Current Signal Transduction Therapy, 2021, *16*, 178-190

RESEARCH ARTICLE

Variational Mode Decomposition Based Retinal Area Detection and Merging of Superpixels in SLO Image

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ARTICLE HISTORY

Received: August 04, 2019
Revised: January 07, 2020
Accepted: January 28, 2020

DOI: 10.2174/1389203721666200218105730

Abstract: ***Background***: Scanning Laser Ophthalmoscope (SLO) image can be used to detect retinal diseases. However detecting retinal area is a major task as retina artefacts such as eyelashes and eyelids are also captured. Huge part of retina can be viewed if it is done with the help of encroachment of SLO.Vision loss can be avoided with the help of retinal disease treatment. In olden days retinal diseases are recognized using manual techniques. Alteration of zooming and contrast are imparted by Optometrists and ophthalmologists. It is done to deduce images and diagnose results based on familiarity and domain knowledge. These diagnostic methods are always a time consuming process. Thus execution time can be reduced using mechanical examination of retinal images. It is better to glimpse at the images which could screen more patients and more unswerving diagnoses can be given in a time efficient manner. Scanning Laser Ophthalmoscope images gives the outcome of 2-D retinal scans. However it contains artefacts such as eyelids and eyelashes along with true retinal area. So the main confront is to eliminate these artefacts from the captured retinal image.

Objective: Scanning Laser Ophthalmoscope (SLO) image can be used to detect retinal diseases. However detecting retinal area is a major task as retina artefacts such as eyelashes and eyelids are also captured. Huge part of retina can be viewed if it is done with the help of encroachment of SLO. In this paper our novel technique helps in detecting the true retinal area based on image processing techniques. To the SLO image two dimensional Variational Mode Decomposition (VMD) is applied.

Methods: In this paper our novel technique helps in detecting the true retinal area based on image processing techniques. To the SLO image two dimensional Variational Mode Decomposition (VMD) is applied. As a result of this different modes are obtained. Mode 1 is chosed as it has high frequency. Then mode1 is pre-processed using median filtering. After this preprocessed mode1 image is grouped into pixels based on regional size and compactness called superpixels. Superpixels are generated to reduce complexity. Superpixel merging is done subsequent to Superpixel generation. It is done to reduce further difficulty and to enhance the speed. From the merged superpixels feature generation is performed using Regional, Gradient and textural features. It is done to eliminate artefacts and to detect the retinal area. Also feature selection will reduce the processing time and increase the speed. A classifier is constructed using Adaptive Network Fuzzy Inference System (ANFIS) for classification of features and its performance is compared with Artificial Neural Network (ANN).

Results: By this novel approach we got a classification accuracy of 98.5%.

Conclusion: Thus 2D-VMD gives six different modes. Based on high frequency mode1 is chosen. This further makes the process easier and it helps to achieve accuracy level higher. ANFIS is able to achieve higher accuracy when compared with ANN. Using ANFIS 98.5.

Keywords: Scanning laser ophthalmoscope, superpixel generation, superpixel merging, classifier construction.

1. INTRODUCTION

Retinal disease treatment helps in avoiding vision loss. Manual techniques were used to detect retinal diseases previously. Better zooming and contrast are imparted by Optometrists and ophthalmologists to give better results. The diagnosis of the process is very time-consuming for each patient. Therefore, a Scanning laser ophthalmoscope is used to avoid this difficulty. Scanning Laser Ophthalmoscope images result in 2-D retinal scans. However, it contains artifacts such as eyelids and eyelashes along with the true retinal area. Therefore, the challenge is to remove the artifacts for a

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better diagnosis. Research was done to segment the retinal area. To detect artifacts, eight directional filter bank is used. The following methods were used previously to detect artifacts. By using eight directional filter bank, shape modeling becomes inaccurate and it is a time consuming process. The first step in detecting is done using edge detection methods such as Sobel, Canny Hough Transform [1] and wavelet transform [2]. To remove eyelashes from the iris, Nonlinear filtering is applied [3].

Gaussian filters [4] and convolution kernels [5] are used to detect eyelashes but the size of the kernel is not fixed therefore, results are inaccurate. Min and Park [6] detected eyelashes using local standard and intensity variation but results were not proper. In Otsu's method [7], eyelashes are detected based on thresholding, but due to variation in the threshold value, results are not accurate. Optic nerve head and fovea [8] structure were also used for the detection of eyelashes but results are not accurate.

Grid analysis is another method used to generate features of the particular region rather than each pixel. However, the exact information about irregular regions in the image cannot be analyzed. Therefore, superpixels are generated for further analysis. The classifier construction is done using ANN SVM and PLS. In PLS classification, results are not accurate. Classification of the retinal area using ANN results in an accuracy of 92.5% [9]. To select improved pixels from the image, superpixel generation is introduced [10]. This technique helps in grouping pixels into different regions depending upon their regional size and compactness. In this paper, the classifier construction is created by analyzing the SLO image-based features.

In our proposed work, VMD is applied in the SLO image. As a result, six different modes are obtained. Mode-1 is chosen because it has a high frequency. This process helps to separate the high frequency region of the image. Mode-1 is preprocessed using median filtering. Then the superpixels are generated. After this, generated superpixels are merged. This helps to reduce the area to be detected and utilize less time for computation. Superpixels are generated to analyze retinal hemorrhage detection [14]. Further feature generation and selection processes are performed. The selected features are classified using ANFIS. Thus, better accuracy of 98.5% is obtained. Our approach helps to increase the speed of computation with less complexity. The paper is structured as follows. Section II gives an insight into our proposed framework. Section III provides the outcome of the work with proof of results and quantitative analysis. Section IV summarizes the work and conclusion of the detection process.

2. PROPOSED METHODOLOGY

A new automatic method for retinal area detection is performed using the Scanning Laser Ophthalmoscope image. Our proposed algorithm for the accurate detection of the retinal area in SLO is explained below.

Proposed Algorithm

i) Scanning Laser Ophthalmoscope images are obtained from the optos database.

ii) Variational Mode Decomposition is applied to the SLO image. This results in different modes.

iii) Choose mode-1 because it has a high frequency.

iv) Group the pixels based on region size

v) and compactness to generate superpixels.

vi) Then the generated superpixels are merged using the message passing algorithm.

vii) Features are generated from the merged superpixels.

viii) Feature selection is done based on the ranking of AUC.

ix) After feature selection, classification is done using ANFIS.

x) The data are trained and tested using

ANFIS.

xi) RMSE is calculated then the Degree of membership curve is plotted which is the output of ANFIS.

xii) The performance graph is compared with ANN and ANFIS and also between superpixel merging and generation.

xiii) Finally, post-processing is done and the retinal area is detected.

The flow chart of the proposed retinal area detector is shown in Fig. (**1**).

2.1. Variational Mode Decomposition

2D-VMD is used because it helps in image segmentation and it is non-recursive [13]. It is free from explicit interpolation and it is adaptive. Higher dimensions are generalized by the gradients and modulation is straight forward. In the EMD band, limits of wavelet are hard and recursive shift limits backward error correction. VMD balances this error [15].

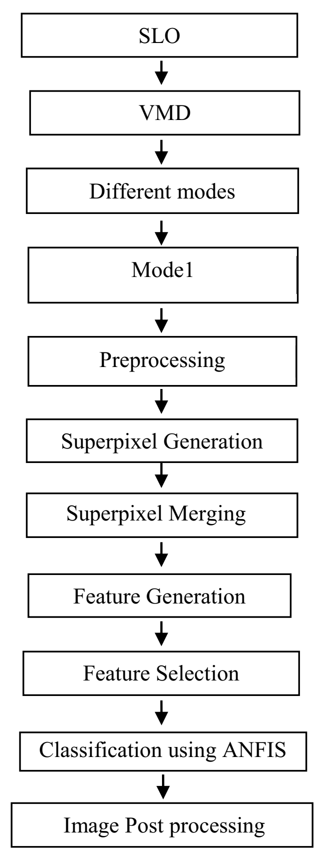


Fig. (1). Flow chart of proposed Retinal Area Detector.

To the SLO image, 2D-VMD is applied. 2D-VMD is an extension to one dimensional VMD. 2D-VMD helps in smoothening the image and it gives sharp edges. The 2D analytical signal is given by a real term and its imaginary term, which is a Hilbert transform.

$$(t)=f(t)+jH\{f\}(t) \tag{1}$$

$\{f\}(t)$ is a Hilbert transform

In spectral-domain, an analytical signal suppresses the negative frequencies and it gives a unilateral spectrum. As a result of VMD, different modes are obtained. Based on frequency, the modes are distinguished and its residue is obtained. Mode 1 has a high frequency. Therefore, it is selected for pre-processing and for further steps.

2.2. Pre-processing

Image pre-processing is done using median filtering. It is nonlinear digital filtering; it helps to remove noise. In median filtering, neighboring pixels are ranked according to the intensity and median value becomes the new value for center pixel. The median is calculated by first sorting all pixel value from the window into numerical order and then replacing pixel being considered with a median pixel value.

2.3. Superpixel Generation

Superpixels are group of pixels which have analogous characteristics. To calculate image features, superpixel algorithm is used which groups pixels into different regions. This formulation will reduce the difficulty of following the image processing task. Severances in image patterns are recognized using superpixels and they provide a scheme of original images.

In this paper, the Simple Linear Iterative Cluster (SLIC) algorithm is used for the superpixel generation [10]. By using the watershed, algorithm superpixels of artifacts are generated more than desired therefore, SLIC is used. It is also computationally skillful in terms of compactness and observance. Clustering is done based on their color similarity and proximity in the image plane. It works with two significant distinctions.

1) The number of distance calculations in optimization is spectacularly condensed. It is done by off-putting search space. This makes the region proportional to superpixel size. Therefore, intricacy to be linear in a number of pixels N is reduced and independent of a number of superpixels.

2) A weighted distance measure joins color and spatial proximity while simultaneously providing control over the size and compactness of superpixels.

Algorithm for SLIC works as follows

I. Compute neighboring matrix $A\sum R^{kXk}$ for all k. Here, A(i,j)=1 i and j are neighbors.

II. Compute diffusion distance $D\sum R^{kXk}$ and average boundary strength matrix $B\sum R^{kXk}$ for all neighboring pixels.

$S=\sqrt{N/K}$ N: Number of superpixels K: Initialisation clusters

2.4. Superpixel Merging

After this, generated superpixels are merged to reduce complexity. Merging is done using Message Passing Algorithm [11]. It lies in splitting the original interference problem into small subproblems. Each subproblem can be solved *via* propagating messages among nodes. Our message passing algorithm do not require Markov Random Field (MRF). It estimates graph structure automatically and label simultaneously unique framework. It works faster as message passing is performed in dual space. This algorithm works as follows.

1. Estimate the current edge. Corresponding solution of structure variables is denoted.
2. During each trial, node pair (i,j) is selected. Variables of the node (i,j) alone are unchanged.
3. The message is passed from node k to node i
4. Accumulated messages are passed from all neighboring nodes to i and also from neighboring nodes to j

2.5. Feature Generation

Next to superpixel merging, the features are determined. It is done to distinguish artifacts and retinal area. Textural, Regional and Gradient features are used for this discrimination [12].

3. TEXTURALFEATURES

Haralick features help to analyze Texture features. It is done by the method of Gray Level Co-occurrence Matrix (GLCM) and it is an algebraic technique. The features calculated using GLCM are cluster shade, cluster prominence, contrast, autocorrelation, difference entropy, dissimilarity, energy, entropy and correlation, homogeneity, information measures 1 and information measures 2, inverse difference normalized, inverse difference moment normalized, maximum probability, sum average, sum entropy, variance and sum of variance. The texture is branded by the spatial distribution of gray levels in the neighborhood. It is a facade property. Dissimilar combinations of pixel gray levels in an image are combined using GLCM. Information about image intensities in pixels are enclosed in Haralick features. Co-occurrence matrices are calculated in directions of 0, 45, 90 and 130.

Contrast measures the number of local changes in the image. It helps in returning the intensity difference between pixel and its neighborhood. Correlation between pixels to its neighborhood is processed using correlation. It helps in measuring gray tone linear dependencies in image. Homogeneity gives information about the pixels which are analogous. Entropy measures the arbitrariness of intensity in an image. Linear reliance in GLCM between identical indexes is defined by Autocorrelation. Cluster shade is defined as a measure of skewness or non-symmetry. Summit in GLCM around mean for non-symmetry is shown by cluster prominence. VAGUE Texture fineness is shown by Local variations. It is defined by contrast. Difference Entropy is defined as a higher weight on a higher difference of index entropy value. Dissimilarity is the privileged weights of GLCM probabilities away from diagonal. The sum of squared elements in GLCM is returned by energy. Information measures 1&2 are entropy measures. Inverse Difference Normalized is the converse of contrast normalized. Normalized Homogeneity is defined by Inverse Difference Moment Normalized. Maximum Probability is the maximum value of GLCM. Higher weights to a higher index of marginal GLCM is defined by Sum average. Higher weight on higher sum of index entropy value is defined by Sum Entropy. Higher weights that differ from the average value of GLCM are defined by Variance. The sum of Variance is defined as higher weights that differ from the entropy value of marginal GLCM. GLCM is applied to each feature. The values are calculated separately for each feature.

4. REGIONAL FEATURES

Superpixels belonging to artifacts have an uneven shape in consideration with those belonging to retinal area so regional features were included. Features labelling regional attributes are area, extent, orientation, solidity, mean intensity and convex area. Number of pixels in Super pixel is defined by area. Extent is the division of area to number of superpixels in bounding box. Number of pixels in convex area of Super pixel is defined by convex area. Orientation is Super pixel angle with reverence to X-axis. Ratio of area to convex area is defined as Solidity. Mean value of super pixel is defined by Mean intensity. The values are calculated separately for each feature.

5. GRADIENT FEATURES

Uneven arrangements of artifacts are highlighted using gradient features. To estimate these features, Gaussian filter bank rejoinder is premeditated. An effective method for removing Gaussian noise is Gaussian smoothing. Gaussian filters are efficient for computation, when rotated in degrees, it is symmetric. Sigma value controls degree of smoothness

Formulas for textural features were provided below

autocorrelation= $\sum_i \sum_j ijp(i,j)$

Homogenity= $\frac{1}{1+(i-j)^2} p(i,j)$

Cluster shade= $\sum_i \sum_j \left(i+j-\mu_x-\mu_y\right)^3 p(i,j)$

Cluster prominence = $\sum_i \sum_j \left(i+j-\mu_x-\mu_y\right)^4 p(i,j)$

Contrast = $\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} |i-j|^2 p(i,j)$

Correlation = $\frac{\sum_i \sum_j (i,j)p(i,j)-\mu_x \mu_y}{\sigma_x \sigma_y}$

Difference entropy= $\sum_{i=0}^{N_g-1} p_{x-y} \log\left(p_{x-y}(i)\right)$

Dissimilarity= $\sum_i \sum_j |i-j| p(i,j)$

Energy= $\sum_i \sum_j p(i,j)^2$

Entropy= $\sum_i \sum_j p(i,j) \log\left(p(i,j)\right)$

Information measure1 $(1-\exp[-2.0(H_{xy}-H)])^{0.5}$

Information measure2 $\frac{Entropy-H_{xy2}}{MAX(H_x,H_y)}$

Inverse difference normalized= $\sum_i \sum_j \frac{p(i,j)}{1+\frac{|i-j|}{N_g}}$

Inverse difference moment normalized= $\sum_i \sum_j \frac{p(i,j)}{1+\frac{(i,j)^2}{N_g}}$

Sum average= $\sum_{i=2}^{2N_g} ip_{x+y}(i)$

Sum entropy= $\sum_{i=2}^{2N_g} p_{x+y} \log p_{x+y}(i)$

Variance = $\sum_i \sum_j (i-\mu)^2 p(i,j)$

Sum of variance= $\sum_{i=2}^{N_g} (i-H_{sum}) p_{x+y}(i)$

Formulas for regional features are provided below

Area = N_s

Extent = $\frac{N_s}{N_{sb}}$

Convex Area = N_{sc}

Orientation = θ_s

Solidity= $\frac{N_s}{N_{sc}}$

Mean Intensity= $I_\mu = \frac{\sum_i \sum_j I_s(i,j)}{N_s}$

6. FEATURE SELECTION

Feature selection is done to explore features and it helps in generating new feature subsets. Computational complexity is reduced with the help of feature selection. It also helps to establish features which are more appropriate for classification. Sequential Forward Selection (SFS) approach is used in this paper. The highest area under curve (AUC) is certain for the available set of features. This process is repeated until ten features were selected. An advanced number of features results in a small improvement of AUC. SFS performance is compared with the" Filter and SFS approach" and "Filter approach". Admittance to all features with minimum data consumption is permitted with the help of SFS. Data utilization is reduced with the help of SFS. It deals with weighted features. SFS works with the following steps.

1) Start by means of blank set X=0
2) Most important features with respect to X are appended constantly.

This process is repeated until the most significant features are included.

Algorithm for SFS filter was provided

1. Begin with empty set $Y_0 = \{\Phi\}$
2. Select the next best feature $X^+ = \text{argmax}[J(Y_k+X)]; X \not\subset Y_k$
3. Update $Y_{k+1} = Y_k + X^+$; k=k+1
4. Go to second step

Formula for SFS filtering

$X^+ = \text{argmax}[J(Y_k+X)]; X \not\subset Y_k$

In SFS filtering, following features were selected and fed as input for ANFIS. They were autocorrelation, difference entropy, sum of variance, variance, sum average, entropy and gradient features.

7. CLASSIFIER CONSTRUCTION

Classifier Construction is done using the Adaptive Network-based Fuzzy Inference System (ANFIS). which is a combination between neural network and fuzzy inference

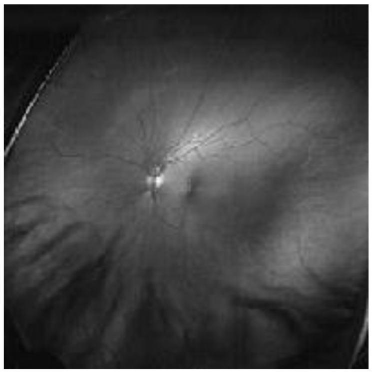


Fig (2). Scanning Laser Opthalmoscope Image.

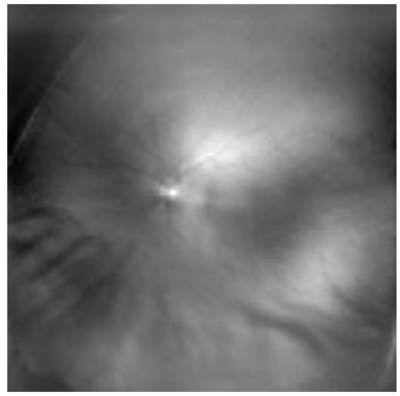


Fig (2a). Mode1 of 2D-VMD.

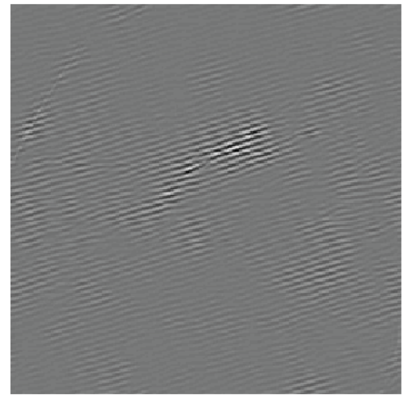


Fig (2b). Mode 2 of 2D-VMD.

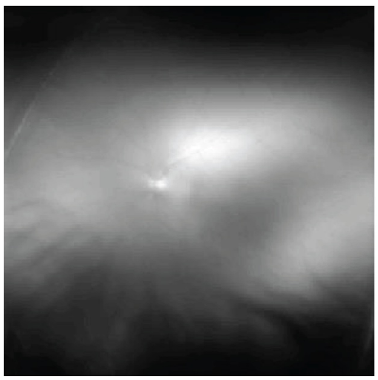


Fig. (2c). Mode 3 of 2D-VMD.

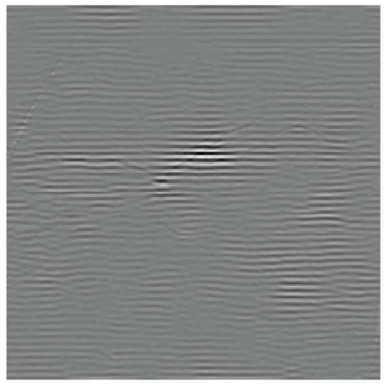


Fig. (2d). Mode 4 of 2D-VMD.

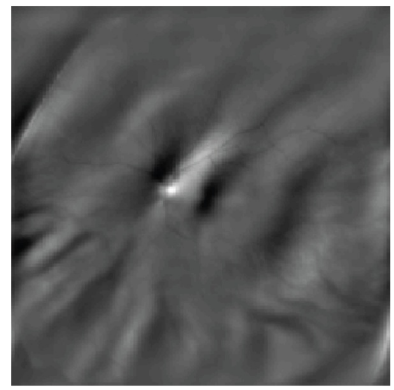


Fig. (2e). Mode 5 of 2D-VMD.

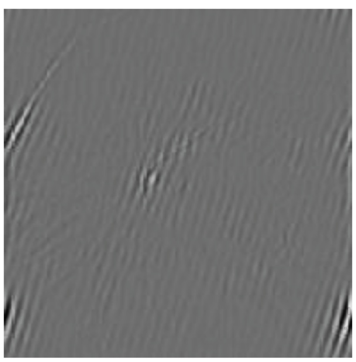


Fig. (2f). Mode6 of 2D-VMD.

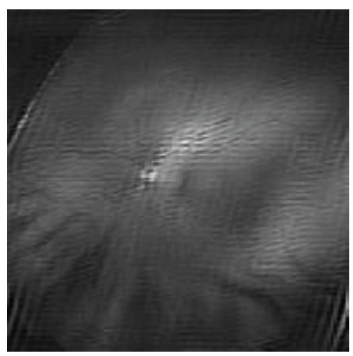


Fig. (2g). Reconstructed composite image.

(*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

system. The selected features were trained and checked from image in optos database. The features which were selected were trained and when checking, the error was calculated. Only selected features were given for input to both ANFIS and RMSE. The output of ANFIS is RMSE whose value is 2.2. RMSE= norm of checked data/ sqrt of checked data. These features were trained and checked for different candidates Preliminary Fuzzy model along with input variables are derived by means of rules extracted from input output data of system being modelled. In this ANFIS technique, the Root Mean Square Error (RMSE) technique is used. It is performed by eliminating all antecedent clauses linked with input variable and then performance is evaluated by checking error criterion. This process is repeated by eliminating another input variable if there is a decrease in modelling error. Eliminated variable is retained and another variable is eliminated if modelling error increases. Here RMSE is minimum.

8. IMAGE POSTPROCESSING

Image postprocessing is performed with the support of morphological filtering. Morphological filtering is a group of nonlinear operations associated with shape. Tiny gaps among superpixels are removed with the help of morphological filtering. Morphological opening is used as operator in this work. Series of operators are defined by morphological filtering. These series of operators perform image transformation by penetrating it with predefined element. The result of operation is determined by junction of pixel neighborhood.

9. RESULTS AND DISCUSSION

The images for performing training and testing are collected from optos database [12]. The dimension of each image is 3900X3072 and the pixels are represented by 8bits. The images in the dataset comprise of both healthy and diseased retinal images. From the database, 70 retinal images are trained, and 26 images are tested and validated using this method. All the retinal image has a resolution of 14µm. In the obtained image, the eyelashes show either dark or bright regions compared to the retinal area. The eyelids show the reflectance region with superior reflectance response in comparison with the retinal area. In our proposed method, the formulation is done to discriminate against the original retinal area and the artifacts in SLO retinal scans.

Following the analysis from the visual representation of the image, the features reflecting the structural and textural regions are the recommended features. These features are computed for different regions in fundus images for the quality analysis. Fig. (**2**) shows the SLO image, which is given as input.

To this input image, 2D-VMD is applied. As a result, six different modes are obtained. The reconstructed composite is obtained if we sum all modes. The solution for 2D-VMD is done using Alternate Direction Method of Multipliers (ADMM) [16]. ADMM is nothing but saddle point of augmented Lagrangian. Modes are differentiated based on frequency. Modes which have high frequency have sharp edges and it is well smoothed. Let the problem be

$$\min_{u_k, w_k} \{ \Sigma \alpha k\ k \parallel \nabla [uAS,k\ (x) e{-}j{<}\omega k,x{>}] \|2\ 2\} \quad (2) \qquad [16]$$

To the above problem ADMM algorithm is applied

$$L(\{uk\}, \{wk\}, \lambda) \coloneqq \Sigma\ \alpha k \parallel \nabla[uAS,k\ (x)e{-}\langle \omega k,x\rangle \parallel 2\ 2 + \parallel f(x) - \Sigma\ uk\ (x) \parallel 2\ 2\ k\ k + \langle \lambda(x), f(x) - \Sigma uk\ k\ (x)\ (3 \quad (3)$$

After applying ADMM algorithm the problem is solved and the result is obtained as

$$\min_{u_k, w_k} \max_{\lambda} (\{uk\}\{Wk\}, \lambda) \quad (4)$$

Among these six different modes are obtained. Mode1 has high frequency and it is selected for further processing. Mode 1 is pre-processed using median filtering. Fig. (**3**) shows the pre-processed image.

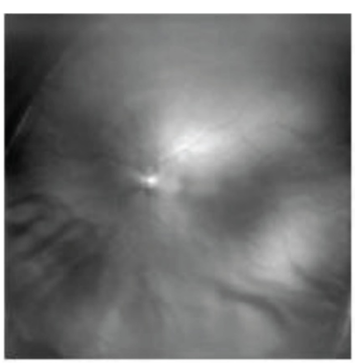


Fig. (3). Pre-processed Image. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Fig. (**4a**) shows a superpixel generated image which is done using SLIC algorithm. This algorithm groups the pixels into various groups that are used to compute features from the image. Grouping superpixels confine the redundancy of the image and obtain a suitable pattern of the image. Simple linear iterative clustering is used in our framework for superpixel generation.

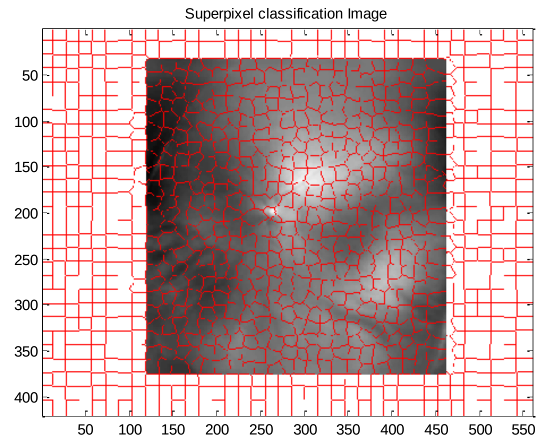


Fig. (4a). Superpixel Generated Image. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

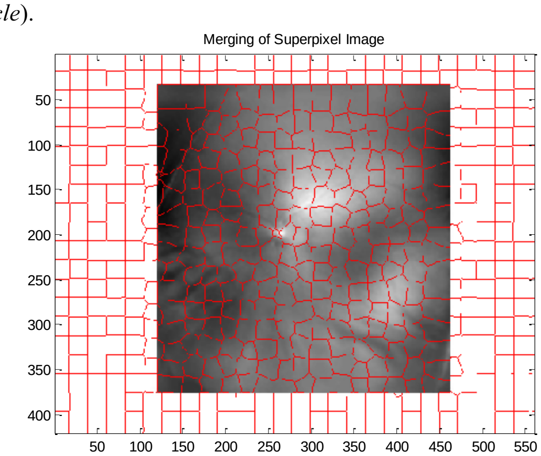


Fig. (4b). Superpixel Merging. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

`Computing cost is reduced by grouping superpixels. It represents different irregular regions in a compact way. By generating a feature vector for each superpixel, the process becomes efficient. Fig. (**4b**) shows the Superpixel merging. Message Passing algorithm is used for Superpixel merging. By this merging process, time is reduced and speed is improved. In the message-passing algorithm, the original problem is divided into subproblems. To each subproblem, a message passing algorithm is applied and finally, messages are accumulated. Then the accumulated messages are passed and finally, superpixels are merged using a message-passing algorithm. By this merging, space and time complexity are reduced hence feature generation is done with the help of these reduced pixels.

To the generated superpixels, message passing algorithm is done. Fig. (**5**) shows gradient filtered image in degrees. Gaussian filter response is used for Gradient filtered image. Fig. (**6**) shows the resultant SFS filtered and the original image.

To make artifacts even, Gradient features are calculated. Hence, it can be removed easily. There are two first order derivatives. They are Ɲx(σ) and Ɲy(σ) in Gaussian filter bank. There are three second order derivatives Ɲxx(σ), Ɲxy(σ) and Ɲyy(σ) in Gaussian filter bank. These derivatives are both in horizontal(x) and in vertical (y) directions. The mean value is obtained for each filter response over the whole pixels of each superpixel. It is done after convolution

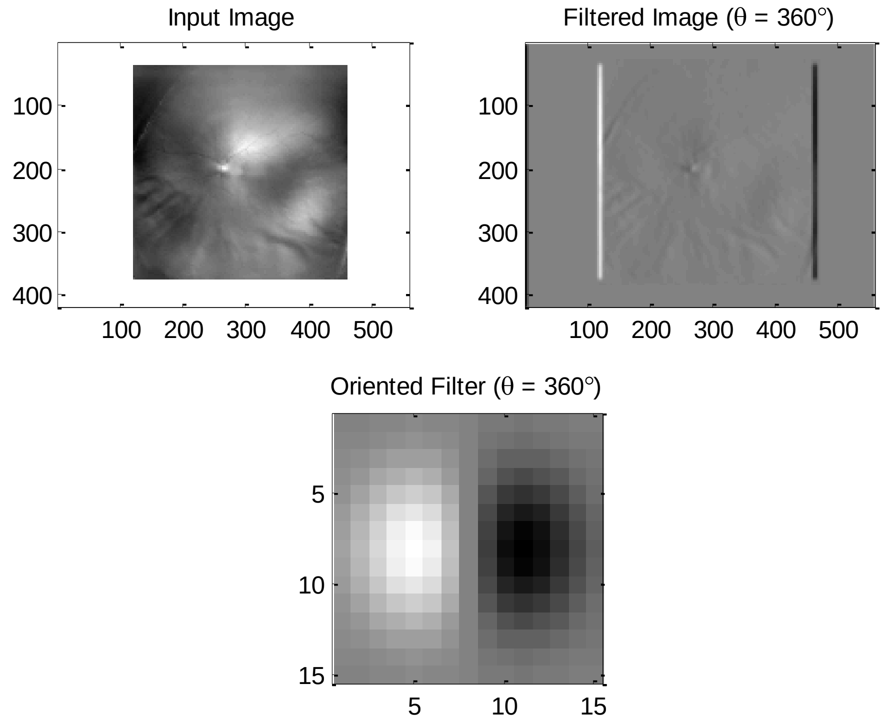


Fig. (5). Gradient filtered Image. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Table 1. Textural Features of mode1.

Textural Features		**Image1**
Autocorrelation		4.016433270676691
Cluster shade		-
-		2.797387467486687
Cluster Prominence		5.325728571498190
Correlation		9.854400023615023
Contrast		1.400717703349282
Difference Entropy		1.645832369572792
Dissimilarity		5.249487354750513
Energy		3.056804442218841
Entropy		1.601903290244610
Homogeneity		9.809655688216060
Information	measures	-
1	-	8.903483141784686
Information	measures	9.609956545959921
2	-	-
Inverse	Difference	9.949457518254512
Normalized	-	-
Inverse	Difference	9.982433821278121
Moment Normalized		-
Maximum Probability		4.975734791524265
Sum average		1.190364832535885
Sum Entropy		1.563274698632190
Variance	-	1.260238858838883
Sum of Variance		4.004861822747565

Table 2. Regional features.

Regional	Features	Mode 1
Mean intensity		1
Area		235200
Convex area		6.152725914418755
Extent		1.202963480356445
Orientation		4.934367452495153
Solidity		9.999999999999980

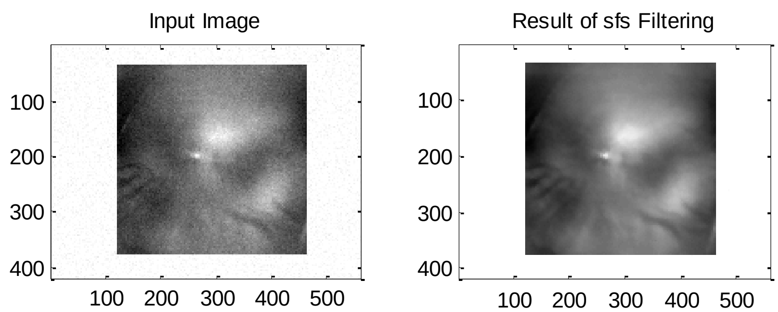


Fig. (6). SFS Filtering. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

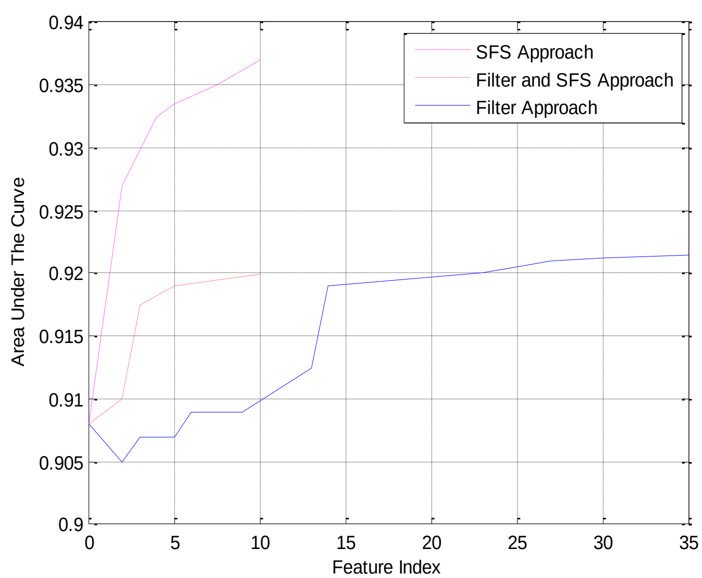


Fig. (7). Comparison of SFS Approach with Filter and Filter and SFS Approach. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

of image. GLCM is used for calculating textural features. All these features are calculated separately. By setting offset value as 1 Haralick features are performed and GLCM matrix was calculated. Table **1** shows the Textual features calculated using GLCM. The features calculated separately for mode 1 images are tabulated for analyzing the performance of the detector.

Regional features are calculated one time for each super pixel. They are not related to channel variation. Table **2** shows calculated Regional features. Mean value of super pixel is defined by Mean intensity. Number of pixels in Super pixel is defined by Area. Number of pixels in convex area of Super pixel is defined by convex area. Extent is the ratio of area to number of super pixels in bounding box. Orientation is Super pixel angle with respect to X-axis. Ratio of area to convex area is defined as Solidity. All these feature values are calculated separately.

Execution time and dimensionality are reduced by feature selection. It helps in the identification of the most relevant features for classification. Most important features are selected using the Feature selection method, which helps to reduce the computational cost. Sequential Forward Selection (SFS) approach is used for the selection of features in our work. In these dealings among features, selected features are taken for consideration. Area under Curve (AUC) for SFS is high when compared with "Filter" and "Filter SFS approach". "Filter and SFS" approach will reduce the number of features that have to be tested through the training of SVM. It is undesirable to discard many features using the "filter and SFS" approach. SFS is a bottom-up algorithm. SFS is a suboptimal search procedure. In SFS, one feature at a time is added to the current feature set. Feature to be included in the feature set is selected. This selection is done

Table 3. Features Selected using feature selection method.

Features Selected	Image1(AUC)	Image2(AUC)
SFS	0.937	0.937
Filter	0.924	0.924
Filter and SFS	0.92	0.92
Approach	-	-

Table 4. Time comparison of algorithms.

Algorithm	Computational Time
ANFIS	0.5S
ANN	0.015S
SVM	8.5S
kNN	1.45S

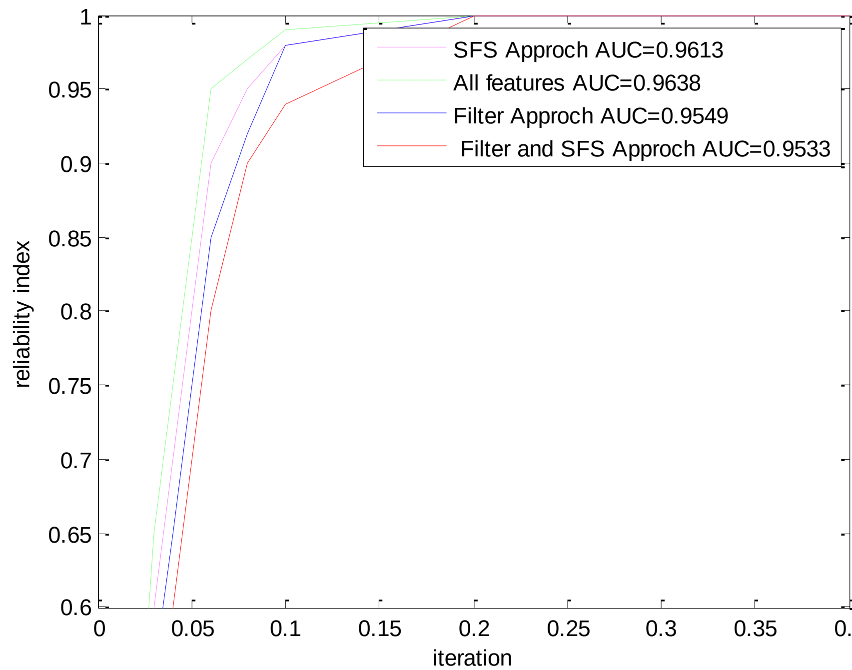


Fig. (8). Comparison of SFS Approach with Filter and Filter and SFS Approach Using ROC. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

from the remaining available features at each stage. The new enlarged feature set yields the maximum value of the criterion function used. SFS starts from the vacant set and selects as the first feature individually which is very fast. The next feature is chosen in such a way that when it is used with the first feature approach chosen, it will give the highest AUC compared to other features. This procedure is repeated further. Fig. (**7**) shows how AUC of SFS is high when compared with the other two methods.

Table **3** shows the features selected using a feature selection method. SFS approach has higher AUC when compared with the "Filter" and "Filter and SFS" approach.

Table **4** shows the time complexity of the proposed approach.

Fig. (**8**) shows the comparison of AUC of SFS with the aid of Receiver Operating Characteristics (ROC). The feature sets include all the calculated features. The other features are preferred by the mentioned approach. The magnified version of comparison of SFS approach with "filter" and "filter and SFS" approach is shown in Fig. (**9**). Fig. (**10**) shows ANFIS selection process.

Fig. (**11**) shows selection of two input from Five candidates and Root Mean Square Error is calculated.

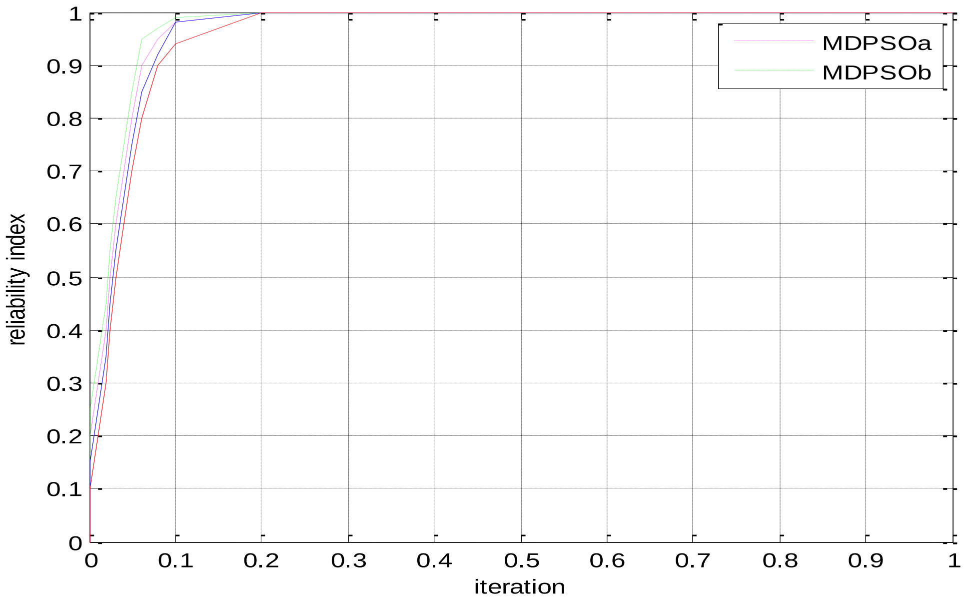


Fig. (9). Magnified version of Comparison of SFS Approach with Filter and Filter and SFS Approach Using ROC. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

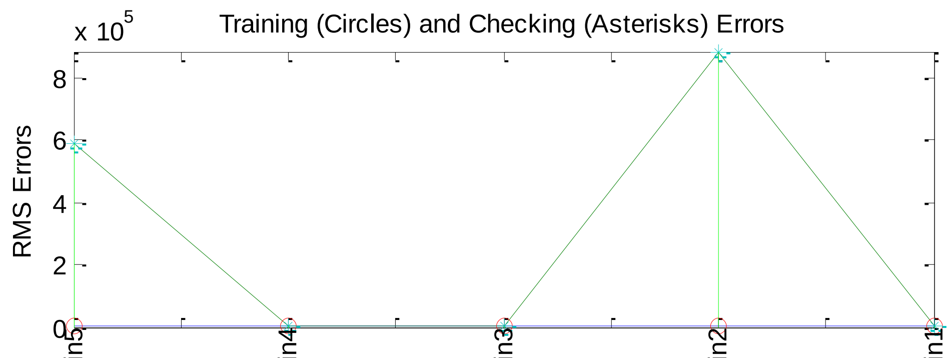


Fig. (10). ANFIS selects one input from Five candidates. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

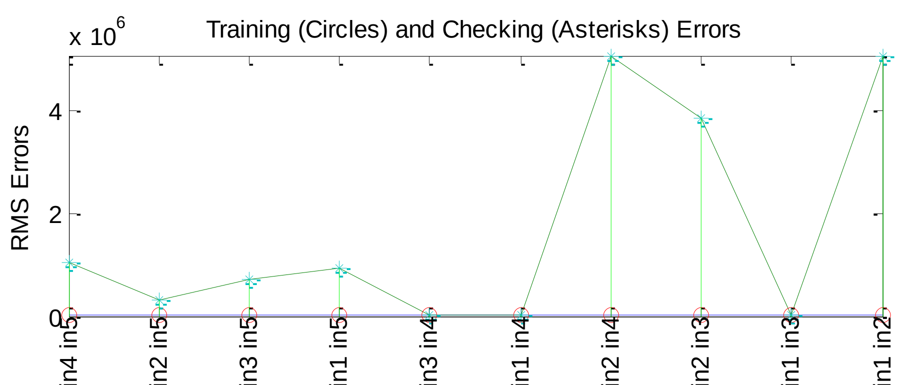


Fig. (11). ANFIS selects Two input from Five candidates. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Fig. (**12**) shows three inputs from Five candidates and their Root Mean Square Error is calculated.

Fig. (**13**) shows Degree of Membership for Five candidates with degrees.

Fig. (**14**) shows the post-processed image, this process is done using morphological filtering. Using morphological filtering, small gaps were removed in superpixels.

Accuracy is calculated by TP+TN/(TP+TN+FP+FN). TP: True Positive, FP: False Positive FN: False Negative, TN: True negative. TP is pixels calculated as retina. TN: artifacts calculated as retina FP: Retina calculated as artifacts. FN: artifacts correctly calculated as artifacts.

Fig. (**15**) shows a comparison of ANN with ANFIS. The accuracy level of ANFIS is 98.5%. The accuracy level of

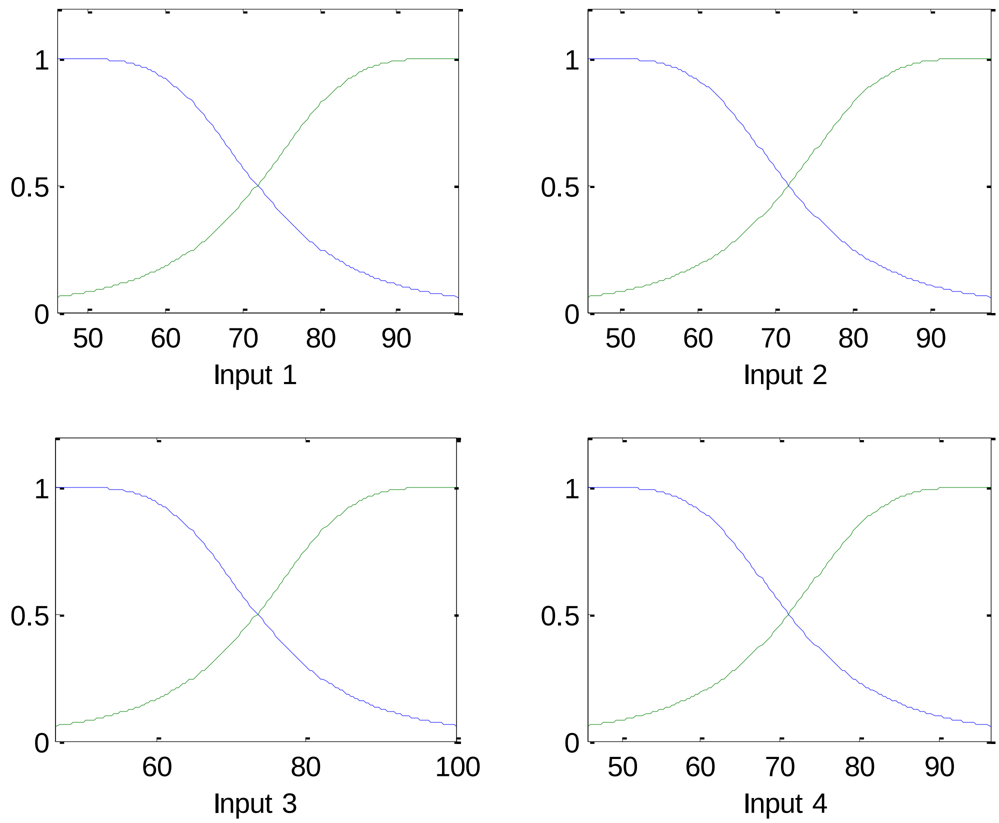


Fig. (12). ANFIS selects Three input from Five candidates. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

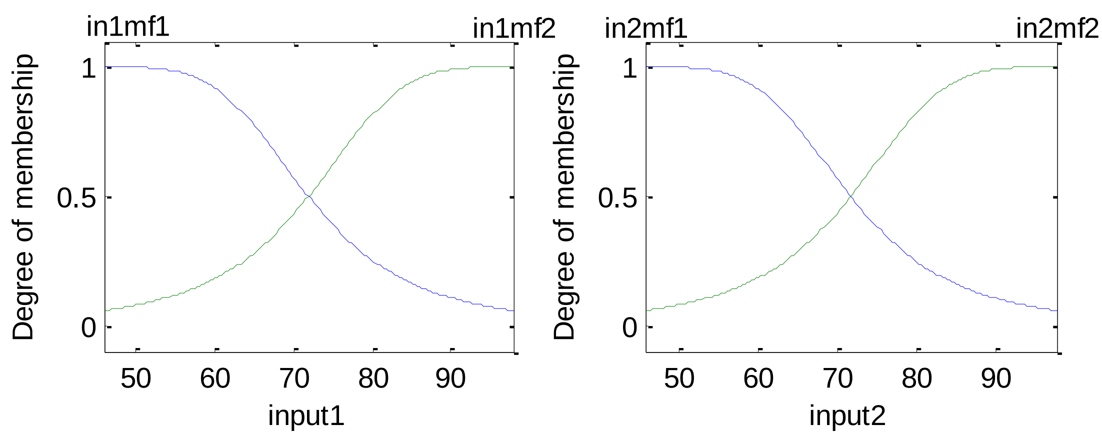


Fig. (13). Degree Of Membership. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

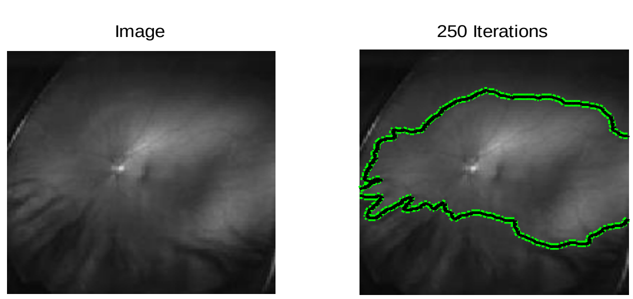


Fig. (14). Post processed Image. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

ANN is 92% Thus in the proposed method by the selection of high frequency and merging the superpixel gave more accuracy in classification. Hence, computational complexity was reduced.

Fig. (**16**) shows a comparison of Superpixel generation and Superpixel merging. After the merging of a superpixel, the accuracy level is improved to 98.5%. Merging reduces the number of superpixels and further process also becomes easier. Time is reduced and speed is increased which in turn helps to increase the performance.

CONCLUSION

Thus, 2D-VMD gives six different modes. Based on high-frequency, mode1 is chosen. This further makes the process easier, and it helps to achieve an accuracy level higher. ANFIS is able to achieve higher accuracy when

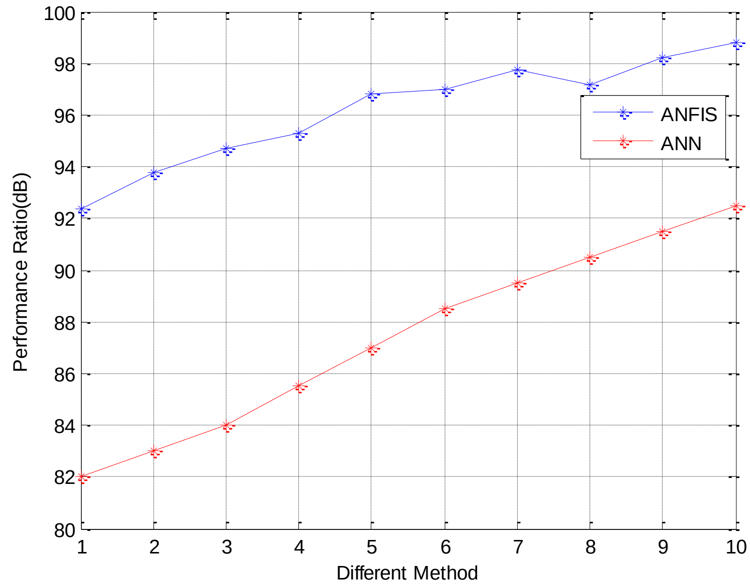
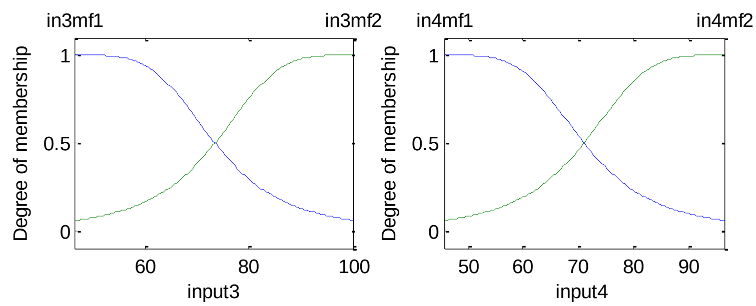


Fig. (15). Comparison of ANN with ANFIS. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).



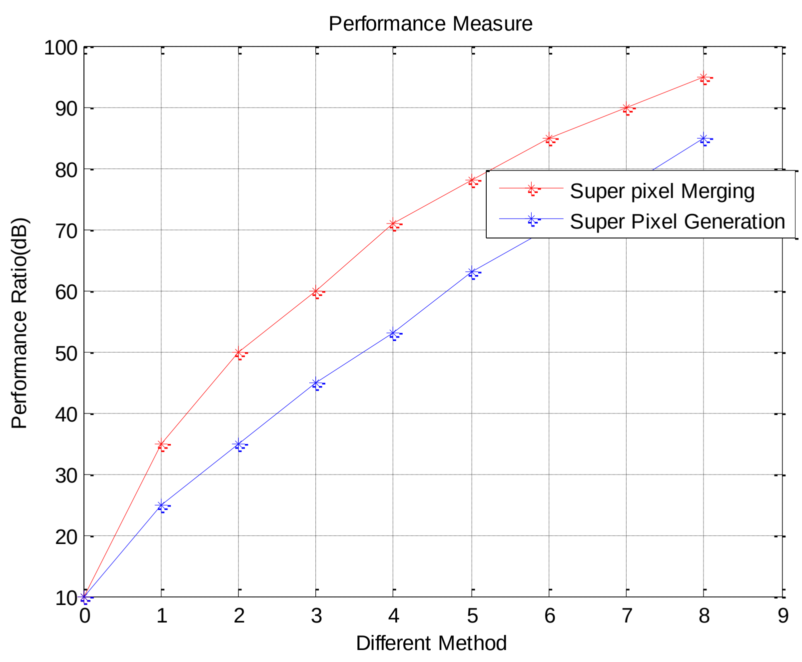


Fig. (16). Comparison between Superpixel merging and Superpixel Generation. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

compared with ANN. Using ANFIS, 98.5% accuracy is obtained. Using ANN, 92% accuracy is obtained. Thus, using RMSE technique errors are checked and degree of membership is plotted. It helps to achieve high accuracy when compared with ANN. By using superpixel merging, accuracy level is improved. By superpixel merging, technique superpixels are further reduced and further feature generation, feature selection and classification are performed which helps to improve performance to 98.5%.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

No animals/humans were used for studies that are the basis of this research.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

FUNDING

None.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

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