Glow Worm Optimization based ANFIS With Mahalanobis Distance for Effective True Blood Vessel Detection

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Abstract—Automated retinal analysis progresses primary recognition and exploration of diseases like diabetic retinopathy. To increase the retinal diagnosis results, the blood vessel segmentation is intricate in most prevailing researches. Conversely the prevailing approaches have noise and exactness concerns. In this paper, Glow worm optimization based ANFIS with Mahalanobis Distance (GWO-ANFIS-MD). Primarily, the image denoising is completed by using Non Local Means (NLM) filter followed by Adaptive Histogram Equalization (AHE) for image development. The appropriate and important structures are removed by using Modified Particle Swarm Optimization (MPSO) with Tabu Search (TS) in retinal images. Then GWO based ANFIS is used to implement the vessel detection more successfully in this research. The investigational result evidences that the vessel detection presentation is greater in terms of advanced accuracy, sensitivity, specificity and f-measure by using the proposed GWO-ANFIS-MD method.

Keywords—Glow Worm Optimization; Non Local Means; Retinal Analysis; Tabu Search Algorithm; Vessel Segmentation.

Abbreviations—Adaptive Histogram Equalization (AHE); Glow worm optimization based ANFIS with Mahalanobis Distance (GWO-ANFIS-MD); Modified Particle Swarm Optimization (MPSO); Non Local Means (NLM); Tabu Search (TS).

I. INTRODUCTION

AUTOMATIC blood vessel detection procedures are known to be labor-saving and time-efficient with advanced accurateness. Performances for blood vessel automated segmentation comprise of matched filter [Odstrcilik et al., 1], model-based [Al-Diri et al., 2], maximum likelihood approximation [Ng et al., 3], and machine learning [Roychowdhury et al., 4]. One of the dissimilar structures of the retina is the blood vessels, whose structure is a significant indicator of disorders such as diabetes, hypertension and cardiovascular disease [Kanski & Bowling, 5]. Retinal imaging has been used to illustrate the vessel structure, and diagnose, monitor and document anomalous conditions [Liew et al., 6]. With current technology, it is previously possible to harvest measureable information of the signs of eye diseases like diabetic retinopathy and glaucoma, as well in many cardiovascular and neurovascular diseases [Abramoff et al., 7]. To qualify automatic or semi-automatic image analysis and the structural characterization of the blood vessels, numerous attitudes have been anticipated for segmenting the vessels from retinal images [Bernardes et al., 8].

In the previous researches, Improved Markov Random Field (IMRF), ANFIS, G-ANFIS, F-ANFIS and AC-ANFIS algorithms have been exploited for true blood vessel segmentation. Amongst the above mentioned methods, the F-ANFIS & AC-ANFIS providing developed concert in terms of presentation measures. Conversely through widespread research it has been originate that the noise and accurateness questions happen due to the performance of minimum iteration. Henceforward in this paper, alternative effective optimization algorithm, the Glow worm optimization is used. Thus the anticipated Glow worm optimization based ANFIS with Mahalanobis Detachment (GWO-ANFIS-MD) is industrialized for proficient true blood vessel segmentation.

II. RELATED WORKS

Staal et al., [9] described a segmentation method based on image ridges abstraction. The ridge pixels are convened into convex sets that represent around straight line fundamentals. Temporarily the authors attained a fundus image database baptized DRIVE from a screening program, which is extensively used for the testing of fundus images dispersion...
technology. Soares et al., [10] accessible a administered method for retinal vessel segmentation; by fashioning a feature vector which contains of pixel intensity and 2-D Gabor wavelet transform rejoiners at multiple scales. Then a Gaussian mixture model is used to classify the image pixel into two classes: vessel point or background.

A scheme expending linear operators and Support vector machines (SVM) is suggested by Ricci & Perfetti in [11]. This algorithm requirements fewer structures and training samples with deference to other overseen method. Lupascu et al., [12] suggested an administered technique expending the Feature-based AdaBoost classifier (FABC), which creates a rich collection of 41-D feature vector and trains an AdaBoost classifier to complete the segmentation of fundus image.

Fraz et al., [13] announced a novel method using bagged and boosted conclusion trees. Initially, a 9-D feature vector is created by gradient vector field, morphological transformation, line strong point measures, and Gabor filter answers. Then the conclusion trees are used as classification model and the consequences of these weak learners are collective using bootstrap aggregation. Marin et al., [14] existing an administered method for retinal vessel detection using a neural network (NN) pattern. Each pixel of the image is symbolized by a 7-D feature vector collected of gray-level and moment invariants-based features. The neural network is qualified on only one database and used to excerpt the blood vessel on multiple databases successfully.

Franklin & Rajan [15, 16] suggested the method of retinal vessel segmentation using multilayer perceptron Artificial Neural Network (ANN). The functional neural network has three layer of one input node, five hidden node and one output node. The input images are preprocessing consuming morphological opening operation, mean filtering and Gaussian filtering. Supervised hierarchical retinal blood vessel segmentation is obtainable by Wang et al., in [17]. Although these patterns seem to be proficient, it is still a challenging work to tradeoff computational proficiency and segmentation exactitude. Thus, a more robust and faster method is required.

**III. PROPOSED METHODOLOGY**

In this section the suggested methodology is elucidated. Primarily, the image denoising is achieved using Non Local Means (NLM) filter while AdaptiveHistogram Equalization (AHE) for image augmentation. Then the OD segmentation is done using Adaptive Markov Random fields (MRF). The features are removed and designated using Modified Particle Swarm Optimization (MPSO) with Tabu Search (TS) in retinal images. Then GWO-ANFIS is used for the vessel detection more successfully in this research.

**3.1. Pre-processing & OD Segmentation**

The NLM filter established by Buades et al., [18] depend on on native pixels between little neighborhood pixels. The converted concentration amount of the picture component is calculated as the weighted normal of all the picture element intensities among the image. Specified a 2D image \( u = i \in I \), the predictable price NLM \((i)\) for a picture element \(i\) is considered as a weighted average of all the pixels concentrations \(u(j)\) in the image \( I \):

\[
NLM(i) = \sum_{j \in I} w(i,j) u(j)
\]

(1)

where the weights \(w(i, j)\) expresses the correspondence amongst the intensities of local neighborhoods \(u(Ni)\) and \(u(Nj)\) attentive on pixels \(i\) and \(j\), such that \(0 \leq w(i, j) \leq 1\) and \(pj w(i, j) = 1\), where \(Nk\) represents a sq. neighborhood of secured size focused at a pel \(k\). This correspondence is restrained as a decreasing function of the weighted Euclidian distance, \(ku(Ni) − u(Nj)k = 22,\sigma, \) where \(\sigma\) is the adjustment of the Speckle kernel. This remoteness is the L2-norm convolved with a Speckle kernel of common place eccentricity \(\sigma\). The weights \(w(i, j)\) are calculated as

\[
w(i,j) = \frac{1}{Z(i)} \exp[-||u(Ni) − u(Nj)||^2_\sigma / h^2]
\]

(2)

Where \(Z(i)\) is the standardising constant

\[
z(i) = \sum_{j \in I} \exp[-||u(Ni) − u(Nj)||^2_\sigma / h^2]
\]

(3)

Where the parameter \(h\) acts as a filtering parameter and controls the decay of the exponential function.

![Figure 1: Overall Proposed Mechanism](image-url)

Then the Adaptive Histogram Equalization (AHE) is exploited for image development and it’s helpful to escalation the distinction within the images. In the adaptive algorithms all pixel is modified based on the pixels that are in a region contiguous that pixel. This region is called contextual region. It has been used to increase contrast images and it is appropriate for improving the local contrast in more detail with over augmented noise.

The suggested classification announced an Adaptive Markov Random fields for OD segmentation process. MRF has long been accepted as a truthful model to characterise the local statistical dependency of image. It affords an
appropriate and dependable way for modelling the spatial-contextual information encompassed in the neighborhood of each pixel. The change uncovering problematic under the MRF framework can be seen as a task of energy minimization. The energy occupation is particular by:

$$E(X_R) = E_{data}(Y_{mn}, X_{mn}) + \lambda E_{sm}(Y_{mn})$$ (4)

Where $E_{data}(Y_{mn}, X_{mn})$ is the different unary energy term, and $E_{sm}(Y_{mn})$ designates the inter-pixels class requirement. $\lambda$ is the smooth weight. $E_{sm}(Y_{mn})$ is communicated in the follow relationship:

$$E_{sm}(Y_{mn}) = \sum_{\{(g,h),(m,n)\} \in E} \delta_k(Y(m,n), Y(g,h))$$ (5)

Where $\{(g,h), (m,n)\} \in E$ characterizes the clique types in the neighborhood. $\delta_k(\cdot)$ is an indicator function. Consequently, the change recognition problematic can thus be explained by conclusion the least energy configuration of the MRF.

3.2. Feature Selection for Retinal Vessel Segmentation using MPSO with Tabu Search algorithm

Amended PSO (MPSO) first uses TS to search, and then it procedures the position of the PSO update mode to increase speed the elements to the optimal solution merging. The Tabu search cans thereby improving the presentation of searching for the optimal solution. The Tabu search chooses the most pivotal solutions from the set of feasible solutions. The Tabu Search algorithm is prearranged as follows:

3.2.1. Algorithm 1: Tabu Search

1. INITIATE
2. Modify feasible solutions $\Omega$; current solution $x$
3. Start with an initial feasible solution $x \in \Omega$
4. Prepare Tabu list $T$ and aspiration level $AL$
5. For fixed amount of iterations Do
6. Produce neighbor solutions $V^* \subset N(x)$
7. Discover best $x^* \in V^*$
8. If move $x$ to $x^*$ is not in $T$ then
9. Consent move and update best solution
10. Modernize $T$ and $AL$
11. Augmentation iteration amount
12. Else
13. If Objective function Cost($x^*$) < $AL$ then
14. Receive move and update best solution
15. Modernize $T$ and $AL$
16. Increment iteration number
17. End if
18. End if
19. End for
20. END

The technique of the offered hybrid model is as follows:

Step 1: The parameter is set, and the population is prepared. Population is prepared randomly, which comprises initialization position $p$ and velocity $V$ of separable.

Step 2: The preliminary suitability assessment of the population is considered by using the objective function, and the fitness value and situation of the global optimal individual are resolute.

Step 3: Tabu search mode is commenced. The new solution is rationalized.

The fitness ideals of new and old individuals are equaled; the better result is particular as a new-generation individual. The objective function (accuracy) is premeditated. The important retinal features are demonstrated.

Step 4: PSO search mode is introduced. The position and velocity of the different are updated, and then a new individual is fashioned. The position and the swiftness are reorganized. Beforehand modernizing the velocity, the inertia weight quantity necessities to be efficient by using

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \frac{iter}{run}$$ (6)

Where $\omega_{iter}$ and $\omega_{run}$ are the current iteration times and maximum iteration times of the algorithm, correspondingly, $\omega_{max}$ and $\omega_{min}$ are the maximum and minimum inertia weights, correspondingly. In a evaluation of the fitness values of new and old personalities, the one with the better result is designated as a new individual, and the global optimal individual is efficient.

Step 5: An $n$-dimensional vector $R_\gamma = [r_1, r_2, ... , r_n]$ is created, and $r_1$ obeys a uniform dissemination with $[0, 1]$. When $r_1 > P_\gamma$, a new individual is randomly produced. In a evaluation amongst the fitness values of the old and new nests, the better one will be designated as a new generation of personalities in the population:

$$Temp_i = Lb + (Ub - Lb) \cdot rand(1, \alpha) \cdot Rf$$ (7)

Step 6: The global and different optimal values are efficient for given images. The optimal positions of all the individuals and whole populations are efficient.

Step 7: If the end circumstance of the algorithm is satisfactory, then the optimal position of the nest is outputted, and the algorithm is concluded; otherwise, Step 3 is achieved.

3.3. Vessel Detection using Glow Worm Optimized ANFIS-MD

The principal stage in relating GWO for training ANFIS’s parameters is to describe the solution space or range of variables to be optimized, a set of restrictions (if have) and the fitness function. Let’s undertake that an input variable is characterized by three fuzzy sets (three Gaussian membership functions). The rules are designed as

$$R_i: IF \ \ x_1 \ \ is \ \ F^1_i (\sigma_{1i}, c_{1i}) \ \ and \ \ x_2 \ \ is \ \ F^2_i (\sigma_{2i}, c_{2i})$$

and

$$x_3 \ \ is \ \ F^3_i (\sigma_{3i}, c_{3i}) \ \ and \ \ x_4 \ \ is \ \ F^4_i (\sigma_{4i}, c_{4i})$$

THEN $y_i = \lambda_{1i} x_1 + \lambda_{2i} x_2 + \lambda_{3i} x_3 + \lambda_{4i} x_4 + \tau_i$

The parameters, which essential to adjust ANFIS, are coded into the different real amount code chain.

In GSO, the luciferin level apprises is observed the most crucial step since the assessment of objective function is executed at the present glowworm position $(Xi)$. For all associates of swarm, the modification of the luciferin level is made based on the values of objective function. The equivalence below is used for the appraise process of luciferin level:

$$L_i(t) = (1 - \rho) L_i(t-1) + \gamma J(X_i(t))$$ (9)
Based on the above comparison, \( L_i(t) \) and \( L_i(t-1) \) symbolize both of the new and old levels of luciferin for glowworm \( i \), individually. Temporarily, \( \rho \) is the luciferin decay perpetual (\( \rho \in (0,1) \)), \( \gamma \) is the luciferin fraction of augmentation, and \( J(X_i(t)) \) signifies the objective function value for glowworm \( i \) at present glowworm position \( (X_i) \) at iteration \( t \). Then, and all through the stage of movement, every glowworm makes endeavor to fascinate the neighbor group \( N_i(t) \) conferring to the levels of luciferin and the range of local resolution \( (rd) \) based on the rule below:

\[
j \in N_i(t), \text{ if } d_{ij} < r_{di} \text{ and } L_j(t) > L_i(t) \tag{10}\]

Where \( j \) designates one of the glowworms close to glowworm \( i \), \( N_i(t) \) characterizes the neighbor group, \( d_{ij} \) represents the Euclidean expanse amongst glowworm \( i \) and glowworm, \( j \), \( d_{ij} \) is the range of local decision for glowworm \( i \), and \( L_j(t) \) and \( L_i(t) \) denote the levels of luciferin for glowworm \( j \) and \( i \), individually. Then, two operations are used to categorize the actual chosen neighbor. These procedures comprise the operation of possibility calculation for conclusion out the direction of movement toward the developed luciferin neighbor. The equation below will be functional:

\[
prob_{ij} = \frac{L_j(t) - L_i(t)}{\sum_{k \in N_i(t)} L_k(t) - L_i(t)} \tag{11}\]

\( j \) characterizes one of the neighbor group \( N_i(t) \) of glowworm \( i \). In the next step, glowworm \( i \) picks out a glowworm from the neighbor group engaging the system of roulette wheel. At this point, glowworm that has developed prospect is more prospective to be elected from the neighbor group. To end with, in the glowworm movement’s stage, adjustment is completed to the position of the glowworm conferring to the chosen neighbor position engaging the equation below:

\[
X_i(t) = X_i(t - 1) + s \frac{x_i(t) - x_i(t)}{\delta_{ij}} \tag{12}\]

Thus the proficient detection of the true vessels is perceived. Grounded on these results the diseases can be recognized.

3.3.1. Steps to Train ANFIS using GWO

Step 1: Preparing of optimization problem and parameters. Prepare input image for ANFIS

Step 2: ANFIS Input pre-treating and parameter initialization

Step 3: Determine the fitness value for each ant using the fitness function

Step 4: Train ANFIS by mean displaying error and search using GWO

Step 5: Return to step 2 until the system fitness meets either fitness. The output is the optimal ANFIS parameters.

Step 6: Re-train ANFIS and expect the true blood vessels

IV. PERFORMANCE EVALUATION

For resounding out the presentation analysis of this work, in the vessel segmentation method, publicly existing datasets, DRIVE with a total of 40 images is exploited. Then the optic disk and vessel segmentation algorithm was established on DRIVE, comprising of a total amount of 60 images. The presentations of this method are afterwards tested alongside several substitute approaches.

For the determination of qualifying the judgement of presentation amongst the Glow worm optimized ANFIS, Ant colony optimized ANFIS-MD, Firefly optimized ANFIS with MD, GANFIS+MD Adaptive Neuro Fuzzy Inference System (ANFIS) with MD and Neural Network (NN) retinal blood vessels segmentation methods, parameters such as exactness, correctness, recall and f-measure are got for the measurement of the presentation of the segmentation.

![Figure 2: Accuracy](image)

Figure 2 displays the comparison of accuracy metric amongst prevailing and proposed methods. It can be understood from this graph that the newly announced GWO-ANFIS-MD has a greater accurateness value rather than the other available system.

![Figure 3: Precision](image)

Figure 3 displays the comparison of exactness metric amongst prevailing and suggested methods. It can be perceived from this graph that the newly familiarized GWO-ANFIS-MD has a greater exactness value rather than the other accessible system.
V. Conclusion

This paper concentrated on the development of automatic retinal image analysis technique based on GWO-ANFIS-MD. The denoising of the images are carried out by making use of NLM filter, image augmentation is talented by construction of Adaptive histogram equalization while Adaptive Markov Random fields used for OD segmentation. Then the MPSO with Tabu Search algorithm for best feature selection and finally the GWO-ANFIS with MD distinguishes the true blood vessels. The suggested pattern is employed for growing superior classification results equated to the other techniques.

References


