# A PSO-ANLBF based Automated Feature Extraction Method


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## DECLARATION

We, hereby declare that this thesis is based on the results found by ourselves. Materials of work found by other researcher are mentioned by reference. This Thesis, neither in whole or in part, has been previously submitted for any degree.

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# CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# ABSTRACT

Image is a much better way of explanation than documentation. The summary of any problem area can be easily described with images. On the other hand, documentation takes much time to make people understood the real problem. With the developing technology, images have been so important in many sectors of the modern world. The medical reports, security verification, boundary measurement- these types of services need very regulable images. Thus image processing is drawing an important role in modern technology. Filtering and feature extraction are the major steps of image processing. There are various types of methods for feature extraction and filtering. Non-local filtering and bilateral filtering are two efficient methods of filtering. We come up with an idea of a hybrid approach of filtering using both non-local and bilateral filtering, called ANLBF (adaptive nonlocal bilateral filtering). The filtering system will efficiently contribute in noise reduction and color enhancement and the output image will be converted into binary image and later will be classified utilizing threshold segmentation. The feature extraction is based on particle swarm optimization technique that helps to reduce the feature vectors. The performance of the proposed approach is acquired using the classification accuracy rate that shows that the approach is effective with minimum 82% accuracy and maximum 91% accuracy rate.

# CHAPTER 01

# INTRODUCTION

## 1.1 Motivations

For the image retrieval problem solving, preprocessing, feature extraction, constructing feature database and matching feature vectors of the query images with the dataset – these tasks are mandatory [1]. The preprocessing step is mainly responsible for denoising and color enhancement. There are different types of noises; like- Gaussian noise, salt and pepper noise, shot noise, film grain etc [2]. There are also bunch of filtering methods for noise reduction; like- linear filtering, nonlocal filtering, bilateral filtering etc. The non-local means (NLM) filtering has fully utilized the large redundancy of natural images and has been successfully applied to low-dose CT imaging [3]. On the other hand, bilateral filtering is a non-linear technique that can blur an image while respecting strong edges and reduces noises, relights, tones mapping [4]. Linear filtering is used for certain type of noises; like, Gaussian noise. Adaptive filter is one type of linear filter but it gives higher accuracy. But non-local filter and bilateral filter are used for different types of noise reduction, bilateral method is better because it achieves high-quality outputs and real-time performances even on high-resolution images and videos [5]. The non-local filter gives the best result when the impulse noise percentage is less than 0.1 %.When the quantity of impulse noise is high the non-local filter does not give the best result [2]. So we brought out the idea of the hybrid method that works jointly with the nonlocal and the bilateral filtering system for reducing noise in a better way.

We have many types of features in an image. The shape, the color, the size all are features for an image. Collecting appropriate information by interpreting the features of an image is basically called feature extraction. In this paper, we propose a particle swarm optimization (PSO) based feature extraction method. This model calculates fewer feature than other feature extraction models but gives a high accuracy rate. Other feature extraction methods, like- SFTA, find out a significant number of threshold values [6]. The proposed model which is inspired from SFTA, gives better result as it reduces the feature vectors and it helps in the computation. The time complexity is also less for the reduced number of feature vectors. The proposed algorithm is constructed with PSO feature selection method. OTSU method could be applied to solve the problem but the time complexity would be increased if the OTSU were used [7]. So, our proposed model is a PSO based feature extraction method which classifies image with comparatively less features.

Table 1 shows the symbols used throughout the paper

**Table 1 – Symbol Table**

| Symbol | Definition |
|---|---|
| $I_A$ | Grayscale Image |
| $I_B$ | Enhanced Image |
| $n_l$ | Gray Level range |
| T | Set of optimized Threshold Values |
| $n_t$ | Number of Threshold |
| B | Binary Image |

## 1.2 Contribution Summary

The summary of the contributions is given below,

- The filtering method is a hybrid of non-local and bilateral filtering system. The proposed model reduces noise from the image and balances color in an efficient way that gives better accuracy.

- The model takes 45 features which is much less than the other feature extraction methods but still the proposed model gives high accuracy rate.

## 1.3 Thesis Orientation

- Chapter 02includes the necessary background information regarding the proposed approaches of PSO-ANLBF based automated feature extraction method.

- Chapter 03 presents the proposed model of our PSO-ANLBF based automated feature extraction approach.

- Chapter 04 demonstrates the experimental results and comparison.

- Chapter 05 concludes the thesis and states the future research directions.

# CHAPTER 02

# BACKGROUND INFORMATION

## 2.1 ANLBF

ANLBF means adaptive nonlocal bilateral filter. It is a filtering system for noise reduction and color enhancement of images. It manages the appropriate contrast of images. ANLBF filtering system is actually a hybrid filtering model came from nonlocal filtering and bilateral filtering.

Bilateral filter is a basic noise reduction technique which was introduced by C. Tomasi and R. Manduchi [8]. This technique is mainly suitable for Gaussian noise reduction. To reduce the noise, this filtering method calculates spatial and intensity difference between a point and its neighboring points [8]. The normalized mathematical equation of this method is given below [8],

$$\mathrm{h(x)} = \mathrm{k}^{\wedge} - 1 \; \mathrm{(x)} \int \mathrm{f}(\xi) \; \mathrm{c}(\xi, \mathrm{x}) \; \mathrm{s}(\; \mathrm{f}(\xi), \mathrm{f(x)} \;) \qquad (1)$$

Here h is output and f is input, $c(\xi,x)$ measures the distance between the neighborhood center x and a nearby point $\xi$. s( $f(\xi)$, f(x) describes the photometric similarity between the pixel at the center x and nearby point $\xi$.

Nonlocal filter is another noise reduction technique which is appropriate for “salt and pepper” noise reduction. This filtering method operates by searching neighboring pixels in a large search space, assigning weights by the similarity of intensity and average pixel intensities with the weight. The normalized equation for non-local filtering is given below,

$$wi = [1/Z(i)\,]\; e \; - \sqrt{}\,[\; 1/S\sum Sk = 1(\| \; yk - zk \; ||)^{\wedge}2] \;/\; h \qquad (2)$$

here z(i) is a constant as $z(i)=\Sigma_i w_i$, $y_k$ and $z_k$ are the values of k $^{th}$ voxels in neighborhoods N and $N_i$. h is a filtering parameter [9].

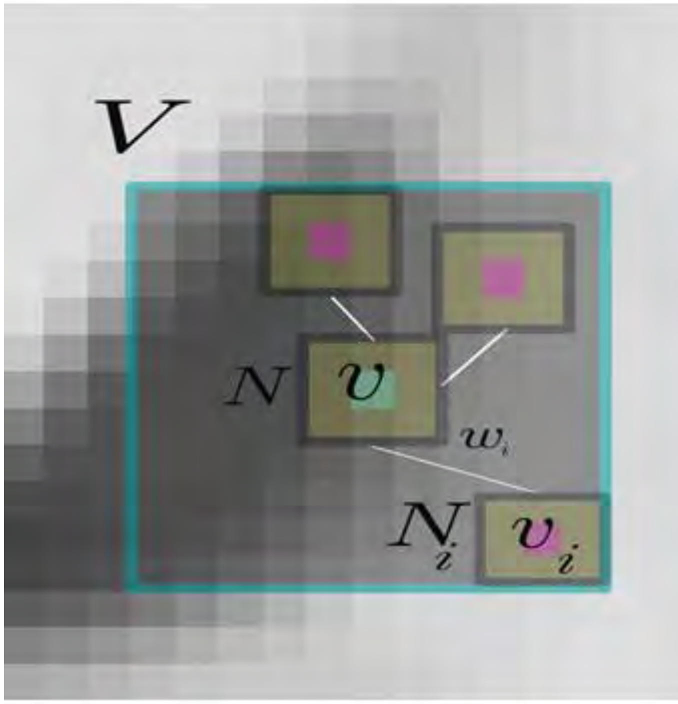


**Fig 2.1**:NLMeans principle: A two-dimensional illustration

Kim et al proposed a model which was a separable implementation of non-local mean filter and adopted bilateral kernel for computing patch similarities [10].Lazcano et al introduced the model that a non-local local gradient based energy is adapted with an extension of bilateral filter to construct disparity map [11]. The idea of a proper adaptive filter mixing the non-local filter and the bilateral filter was improvised to get a better accuracy in denoising the images [12]. ANLBF is the hybrid model of non-local and, bilateral filtering method that tries to take the benefits and cuts out the drawbacks of non-local mean and bilateral filters.

## 2.2 Particle swarm optimization

Particle swarm optimizer is an optimum solver which is derivative free around the globe. In this algorithm, each particle is primitive. The particles only know their present location in the search space, their previously best location and the overall best location found in the 'swarm'. No gradients to be solved in this optimum solving process. With each iteration, the particles move towards the global optimum. The coordinating and coherence level is surprising in this computational swarm. Particle swarm optimization allows binary optimization and it is modular and customizable. This optimization process has vectored fitness functions.

## 2.3 SFTA

In the time domain, the vibration time signal samples are used to be displayed in the 2D dimension. At first, a matrix is constructed with the sample signal values by segmenting the signal into equal length subparts. The subparts are arranged as the column of the matrix. The subpart length decides the height of the matrix and the number of subparts decides the width of the matrix. Lastly, the sample values are normalized within the range of 0-255 of grey-level image and the matrix converts into an image.

*SFTA extraction algorithm :*

SFTA extraction algorithm is shown by figure 2.2. At first, gray level image is taken as input. Then feature vector is generated according to the size of the resulting binary images, boundaries' fractal dimension and mean gray level. A border image is represented by the boundaries of a binary image

$I_b$(x, y) [13] which is denoted by Δ(x, y). It is computed as follows,

$$(x, y) = \begin{cases} 1 \; if \; \exists \, (x', y') \in N8[(x, y)]: \\ \quad I_b(x', y') = 0 \, \Lambda \\ \quad I_b(x \, , y) = 1 \\ \quad 0, otherwise \end{cases} \qquad (3)$$

Δ(x, y) grabs the value 1 if the pixel is at (x, y) position in the binary image. $I_b$ (x, y) has value 1 and has at least one neighboring pixel having value 0. Otherwise, the value 0 is taken by Δ(x, y). Using the box counting algorithm, fractal dimension D is computed from each border image. Figure 2.2 explains the SFAT feature extraction method,

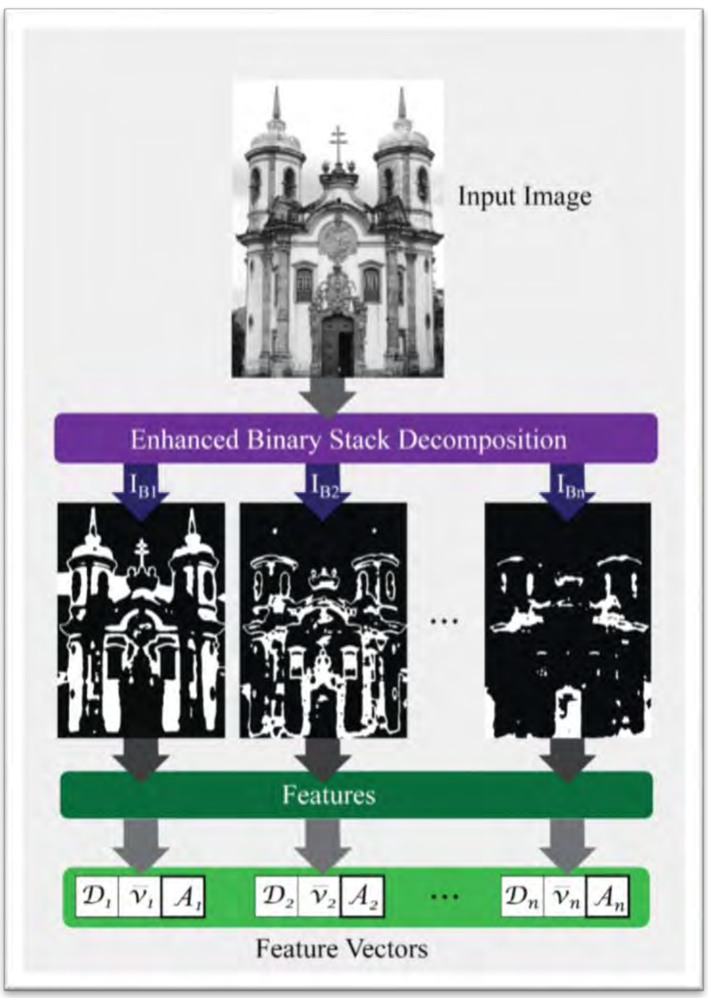


**Fig 2.2 :** SFTA extraction method

The input image was converted into binary images by Two-Threshold Binary Decomposition algorithm [13]. Then resulting binary images' size, mean grey level were used to form the SFTA feature vector [13].

# CHAPTER 03

# PROPOSED PSO-ANLBF BASED AUTOMATED FEATURE EXTRACTION APPROACH

## 3.1 Introduction

Figure 3.1 illustrates a detailed implementation of our proposed model. It demonstrates how our algorithm is going to work. For making generalized model for feature extraction, if any RGB images are there for this model, first it will convert them into grey level images. If it is grey level already it will start directly the steps without requiring any conversion. Then we perform basic histogram equalization to make the balance of the contrast of those images in the pre-processing step. Then we apply our proposed ANLBF to remove noises from high contrast images and to enhance them again. Next we use Particle Swarm Optimization in our model. A two-threshold decomposition technique is applied to obtain number of binary images. The borders of the images and their features, the fractal dimension of the images and mean of grey level are computed for each binary image to accumulate feature vectors. Finally SVM classifier is used for detecting abnormality.

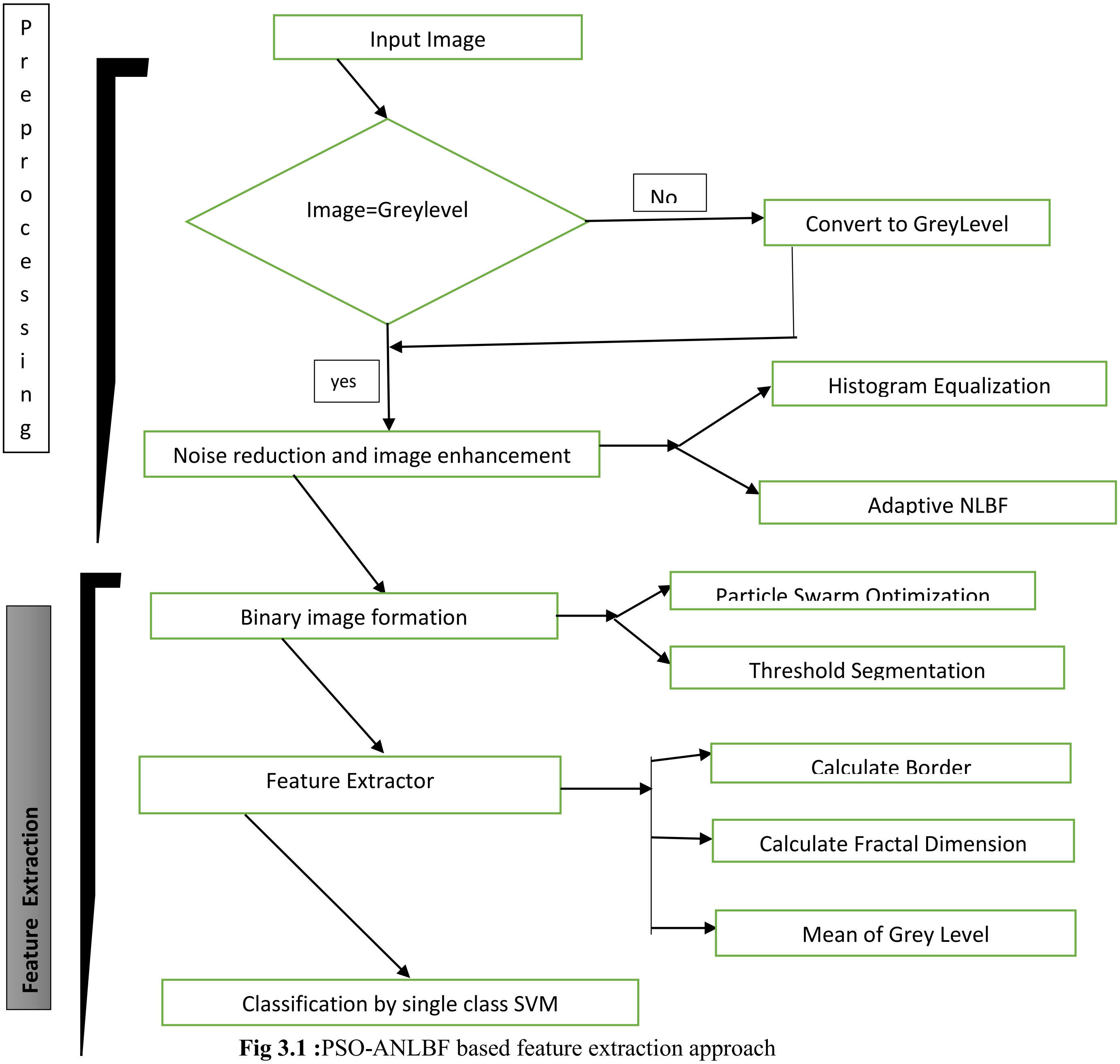


**Fig 3.1 :**PSO-ANLBF based feature extraction approach

## 3.2 Histogram Equalization

Histogram equalization is the method for increasing global contrast of images where close contrast values are present. This technique is mainly used to adjust image intensities to enhance light, color, contrast. We try to maximize the image contrast by applying a grey level transformation. It is a scaled version of the original image's cumulative histogram. The grey level transform Z is given by,

Z[t] = (C-1)d(t)

Where C = the number of grey levels

d(t) = the normalized histogram of the original image [14]

For a given image I represented as wr by wc matrix of integer pixel intensities. It ranges from 0 to V-1.

V = the number of possible intensity values

Let, r = the normalized histogram of i

$$\text{So, } rx = \frac{\text{number of pixels with intensity x}}{\text{total number of pixels}}$$

x = 0, 1,….., V-1.

The histogram equalized image h will be defined as,

$$hp,q = \text{floor}\left(( V\text{-}1 )\sum_{x=0}^{i\ p,q} rx\right) \qquad (4)$$

where floor() rounds down to the closest integer.

This is equivalent to transforming pixel intensities, t, of i by the function

$$S(t) = \text{floor}((V-1)\sum_{x=0}^{t} rx) \qquad (5)$$

This transformation comes from thinking of the intensities of i and h as continuous random variables A, B on [0, V − 1] with B defined by

$$B = S(A) = (V - 1)\int_0^A rA(a)da, \qquad (6)$$

Where rA = probability density function of i

S = cumulative distributive function of A multiplied by (V − 1).

For simplicity we assume that S is differentiable and invertible. It can then be shown that B defined by S(A) is uniformly distributed on [0, V − 1], namely that rB (b) = $\frac{1}{V-1}$ [15]

### 3.3 Adaptive NLBF

We sometimes observe noises which are visible for high contrast images after histogram equalization is performed. To get rid of this problem by removing noise from images and by enhancing it once again, we use ANLBF. ANLBF normally picks locality with non-local mean perception to restructure the boundaries. To perform the bilateral filtering in this technique we need to declare neighbors for each pixel of the noisy image. Next we calculate the weights of the neighbors to find out similarity from that. It is easier to declare the similar neighbors to perform the bilateral filtering based on those similarities. We calculate peak signal to noise ratio (PSNR) in NLBF. PSNR is the proportion flanked by the location signal and the alteration signal of an input image.

#### Non-Local Filter

Removing noise from image is a classic signal processing problem. In additional noise model, noise image $u$ is result of addition of noise $n$ to original image $v$ :

$$u(y) = v(y) + n(y)$$

Denoising process is to obtain $v$ from $u$ [16]

Image $v$ needs to be recovered from input image $u$ .Neighborhood filter proposed by Yaroslavsky [4] selects a set of pixels $J(y)$ for each pixel $y$ in input image Ω. The set is defined by spatial close to $y$ and similarity of intensive value with $u(y)$ . Mean of $u$ for pixels of the set $J(y)$ in discrete form is applied for all pixels:

$$NHu(y) = \frac{1}{|J(y)|} \sum_{x \in J(y)} u(x) \qquad (7)$$

The Gaussian filter is a smoothing filter but at the cost of less distinct edges . [18] Then it becomes a base for other filters which are called by ‘sigma-filters where similarity weight function depends on similarity of pixels *x* and *y* [19]

$$w(x, y) = exp(-\frac{G(||u(x=.)-u(y+.)||^{\ 2})}{h^2}) \qquad (8)$$

and the normalization factor over neighbors :

$$C(x) = \int_{N(x)} w(x, y)\, dy \qquad (9)$$

**Bilateral Filter**

Aurich and Weule [20] employed non-linear filters which combines the aspects of anisotropic diffusion and robust filtering basing on Gaussian filters with parameter to increase noise reduction and filter scale of the spatial and intensity respectively.

*Nx*is renormalization factor:

$$\text{Nx}=\sum_{yeBr(x)} G\left(||x-y||\right)(u(x)-v(x)) \qquad (10)$$

Tomasi and Manduchi introduced bilateral filter [21] with global constants which smooths surfaces, just as the Gaussian Filter, while maintaining sharp edges in the image.

**For Denoising Gray Image**

The conditions of spatial neighborhood and intensity similarity are presented in the first and the second Gaussian filter of the bilateral filter . The threshold supports to refine neighbors selection with the most similar intensive value. The search field is replaced by non-local neighborhood by similarity weight . This is major introduction of non-local concept into a new adaptive bilateral filter. [22]

### 3.4 Binary Image Formation

In the next step we obtain the feature vector from the pre-processed image in order to develop some set of binary images from that original one. After establishing desired number of binary images through different levels of thresholding, segmentation process is applied on each image to estimate the overall feature vector.

**Particle Swarm Optimization**

For the multilevel threshold, we use Particle Swarm Optimization in our model in stead of using conventional Otsu thresholding.PSO (Particle Swarm Optimization) consists of a set of solutions, which is known as swarm or population. Each solution consists of a set of parameters and represents a point in the multidimensional space, denoted as a particle [23]. The velocity of the particles are adjusted based on the previous behavior of each particle and its neighbors while travelling through the search space. A particle's motion is mainly affected by two things. One is it's current position and another one is it's memory of previous useful parameters along with the cooperation and knowledge of the swarm [24, 25]. For this reason, the particles have a tendency to fly towards a better search area over the search process course [26]. Each particle continually adjusts its speed and trajectory in the search space based on this information, moving closer towards the global optimum with each iteration. The velocity of the i-th particle in the k-th iteration is determined as follows:

$$V_{id}^{k+1} = UV_{id}^{k} + m_1 n_1\left(tb_{id}^{k} - x_{id}^{k}\right) + m_2 n_2\left(jb_{id}^{k} - x_{id}^{k}\right) \tag{11}$$

Where $m_1$ and $m_2$are acceleration constants and $n_1$ and $n_2$ are random values in the range of 0 and 1. The parameter U is the inertia weight. The parameter shows the position of each particle in the d-dimensional search space [24].

The parameter U (eq. 4) is regarded as the inertia weight. The parameter $x_{id}^{k}$shows the position of each particle in the d-dimensional search space. The best previous position of each particle is represented by $tb_{id}^{k}$ and considered as particle best position.$j_{d}^{k}$is the best position of all particles, being denoted as global best particle [18]. The i-th particle position is updated by:

$$x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k} \tag{12}$$

PSO reveals an effect of implicit communication between particles by updating neighborhood and global information, which affect the velocity and consequent position of particles [23].

**Threshold Segmentation**

We have repeated the process till the desired number of threshold parameter has been found by the user, The user will define the parameter for desired number of threshold values based on trial and test. Further, a two-threshold decomposition technique is applied to obtain number of binary images. A simple method for automatic threshold selection is to detect the valley of the gray-level histogram [27]–[28].

This technique can be expressed as:

T=T[x, y, m(x, y), n(x, y]

Where: T is the threshold value.

x, y are the coordinates of the threshold value point.

m(x,y) ,n(x,y) are points the gray level image pixels. [29]

We consider image p(x) having N gray levels , where p(x) is the gray level at position x . If the class labels is denoted as Dp, Dq representing the classes of object and background respectively [30] . Then, the thresholding operation is defined as follows:

Dx={Dp,   if t(x) > Q

Do,     otherwise

where ,

Dx = the label at position x

Q  = the threshold

t(x) = the decision function

### 3.5 Feature Extractor

For feature extraction, three features: the borders of the images and their features, the fractal dimension of the images and mean of grey level are computed for each binary image. Such computation accumulates feature vectors.

According to the conventional SFTA; the number of causing binary images is *2n* [26]; where *n* means number of thresholds. There is a problem regarding the number of the subsequent binary images. On practical work, the number is not *2n*, it is *(2n-1).*With relating the two threshold segmentation to the input image; the set of binary image is obtained. All pairs of adjoining thresholds from $T \cup \{np\}$ and all pairs of thresholds $\{t,np\}$, $t \in T$, is used in this process where *np* corresponds to the maximum possible gray level in *I(x, y)*. Here *np* stands for gray level range; *T* for threshold. This way, finally, the number of resulting binary images is *2n -1*

For example, if the required number of threshold is 4, on the conventional SFTA; the causing binary image would be 8 but according to the correct and practical approach it would be 7. Proposed number of binary image will be 7 which means it will follow this 2n-1 rule by which we get 2*4-1=7 . The feature vector will be of 27 values depending on three features which are

Calculating Border , Calculate Fractal Dimension and Mean of Grey Level. Fig 3.4 shows the detail process of this [27].

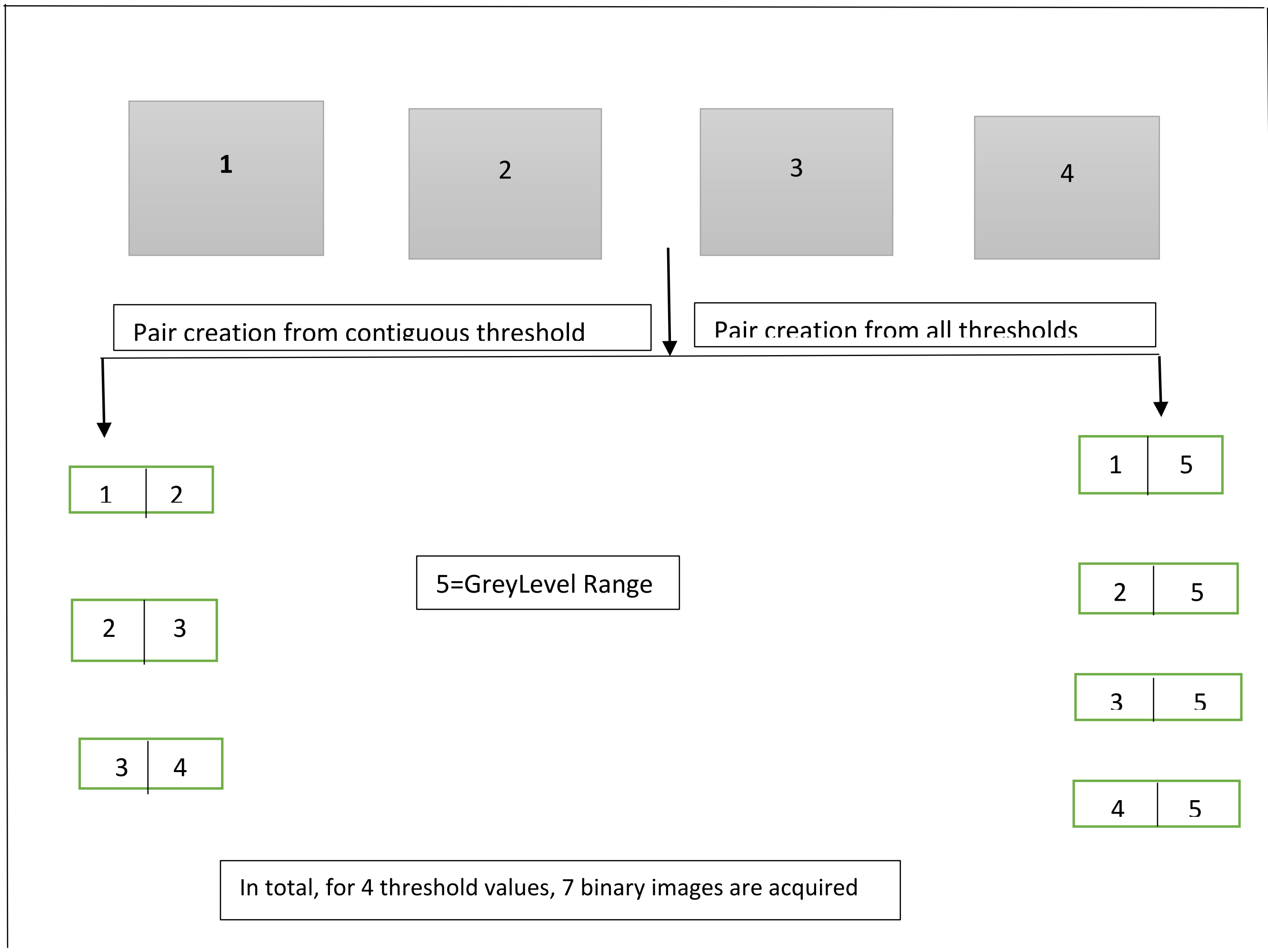


**Fig 3.4**: Exact Binary Image Formation Process from Threshold

Steps in algorithm of our proposed model is as below :

| | | | |
|---|---|---|---|
| *01.* | *Image, $I_A$* | $\leftarrow$ | ***Histogram Equalization** (I)* |
| *02* | *Enhanced Image, $I_B$* | $\leftarrow$ | ***ANLBF**($I_A$)* |
| *03* | *Threshold, T* | $\leftarrow$ | ***PSO**($I_B$,$n_t$)* |
| *04.* | *Set 1 from binary images, P* | $\leftarrow$ | $\{\{tk, t_{k+1} \in T, k \in [1..\vert T \vert - 1]\}$ |

| | | | |
|---|---|---|---|
| *05.* | *Set 2 from binary images, N* | ← | *{{$t_k$, $n_l$}:$t_k$∈T, k ∈[1...\| T \|]}* |
| *06.* | *K* | ← | *0* |
| *07.* | ***for** {{lower threshold, upper threshold}:{lower threshold, upper threshold} ∈P UN}* | | ***Do*** |
| *08.* | *Binary Image, $B_i$* | ← | ***Threshold Segmentation** ($I_B$, lower threshold, upper threshold)* |
| *09.* | *Border Image (x, y)* | ← | ***Border** ($B_i$)* |
| *10.* | *Feature Vector[k]* | ← | ***Calculate Fractal Dimension** ($B_i$)* |
| *11.* | *Feature Vector [k + 1]* | ← | ***MGL** ($I_B$, $B_i$)* |
| *12.* | *Feature Vector [k + 2]* | ← | ***Pixel** ($B_i$)* |
| *13.* | *K* | ← | *k+3* |
| *14.* | | | ***end for*** |
| *15.* | ***return*** | | *Feature Vector* |

# CHAPTER 04

# EXPERIMENTAL ANALYSIS

## 4.1 Introduction

Fig 3.1 explains our proposed model. It illustrates the proposed algorithm. The figure shows how the pre-processing step and the feature extraction process has been done. At first, we covert the input image into grey level image, enhance contrast by histogram equalization and denoise it by ANLBF method in the pre-processing step. Then we construct the SFTA algorithm for our proposed model and finally apply the algorithm in the feature extraction step.

For our proposed algorithm, we used MATLAB 14 and Microsoft EXCEL 13 for statistical calculations. The graphics hardware specification is, AMD RADEON R5 M430. All experiments are done in a personal computer with configuration of Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz, 4 GB RAM , windows 10. Two publicly available dataset were used to test our model- BRAINIX [31] and Texture dataset [32].

## 4.2 BRAINIX Dataset

MRI images from BRAINIX dataset is evaluated on a series of 22 images of a single patient. Fig 4.1 shows some sample images from BRAINIX dataset.

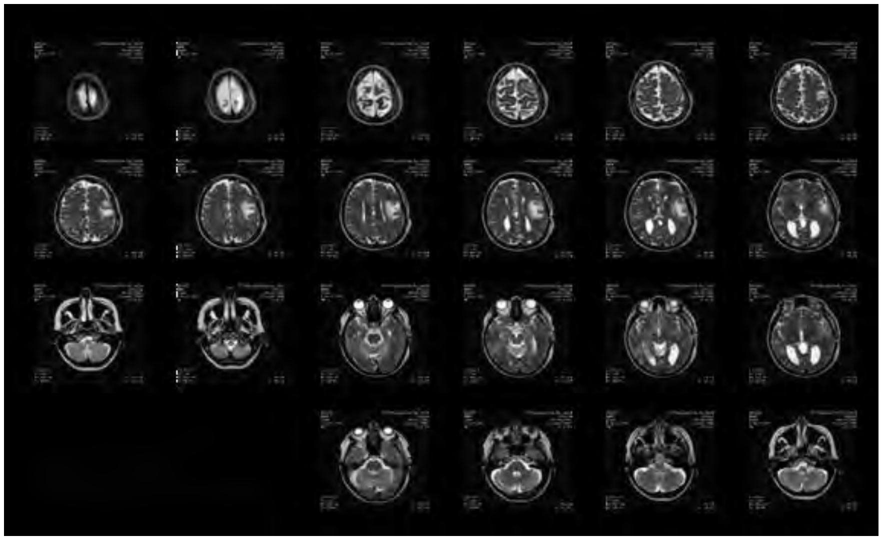

**Fig 4.1**: sample images from BRAINIX dataset

### 4.3 Texture Surfaces Dataset

Texture surfaces dataset has different surfaces composed with materials, like- marble, wood and fur under varying scales, viewpoints and illumination conditions. Fig 4.2 shows some sample images of this dataset,

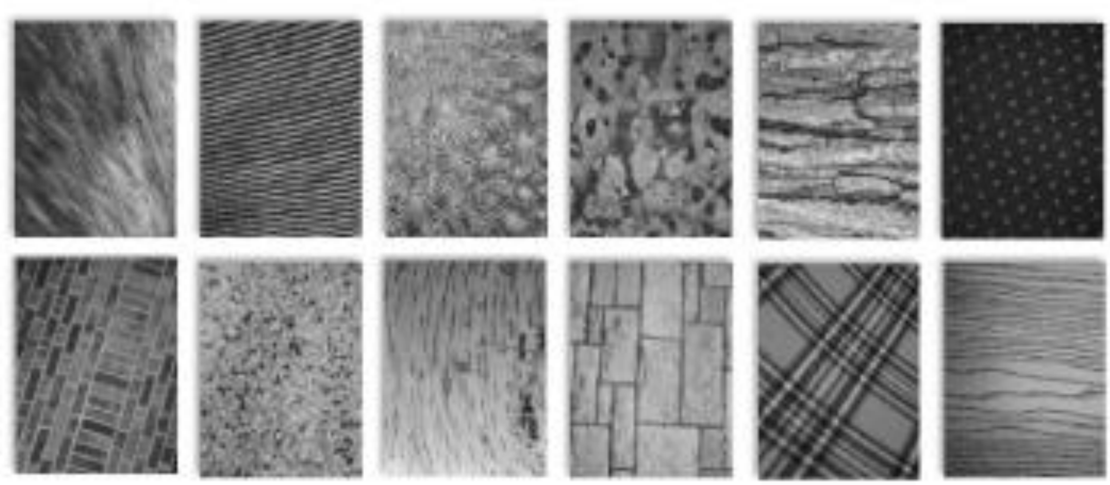

**Fig 4.2:** sample images from texture surfaces dataset.

### 4.4 Experimental Result Analysis

For texture surface dataset, we perform the pre-processing technique. After the pre-processing done, according the proposed approach, we need to determine the threshold values to calcite the number of binary images. From those binary images, we calculate the feature vector and we perform the classification. We considered 3 to 8 threshold values for this scenario. For threshold value 3, we got 5 binary images and 15 feature vectors. If the number of threshold value is $n$ then the number of feature vector will be $2n - 1$ and feature vector will be $3 * (2n - 1)$. According to this formula, we calculate the number of feature vector. For each case we calculated the classification accuracy. In this case, when the feature vector number is 6, then the best classification accuracy came.

**Table 2-** accuracy table for texture surfaces dataset

| Number of Threshold values | Feature Vectors | Accuracy (%) |
|---|---|---|
| 3 | 15 | 71.5 |
| 4 | 21 | 77 |
| 5 | 27 | 85 |
| 6 | 33 | 91 |
| 7 | 39 | 91 |
| 8 | 45 | 91 |

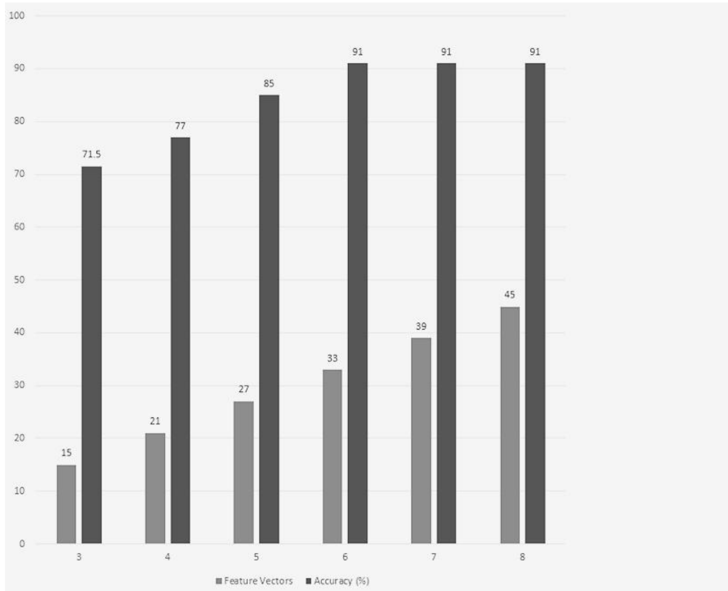


**Fig 4.3**: accuracy based on feature vector number for texture surface dataset

From Fig 4.3, it is clearly visible that when the feature vector number is 33, then the classification accuracy is 91%. After that it remains constant because from each binary images, after that 33 features no unique features has been added to the total feature vector. As there are no unique features has been added, the output remains same. So for this dataset, our experimental result validates 91% accuracy for the classification.

After this classification accuracy, we considered MRI dataset for the classification purpose. For BRAINIX dataset, we have considered the same set up for dataset 1. In this case also we considered threshold 3 to 8 threshold values for this scenario.

**Table 3**- accuracy table for BRAINIX dataset

| Number of Threshold values | Feature Vectors | Accuracy (%) |
|---|---|---|
| 3 | 15 | 65.5 |
| 4 | 21 | 71.2 |
| 5 | 27 | 75 |
| 6 | 33 | 78 |
| 7 | 39 | 82 |
| 8 | 45 | 82 |

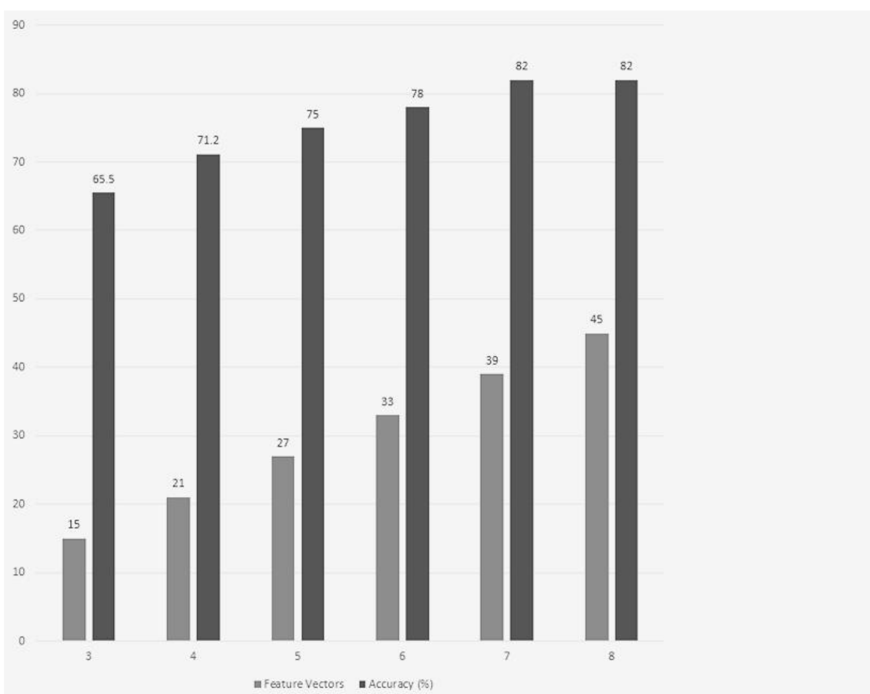


**Fig 4.4**: accuracy based on feature vector number for MRI dataset.

From Fig 4.4, it is clearly visible that when the feature vector number is 39, then the classification accuracy is 82%. After that it remains constant because from each binary images, after that 39 features no unique features has been added to the total feature vector. As there are no unique features has been added, the output remains same. So for this dataset, our experimental result validates 82% accuracy for the classification. This dataset though did not perform well, still the overall classification accuracy remains 82% which is satisfactory if we think about the feature vector number we have considered.

# CHAPTER 05

# CONCLUSIONS AND FUTURE WORKS

## 5.1 Concluding Remarks

Our proposed model shows that our approach of ANLBF filtering and SFTA feature extraction brings much accuracy in image classification. The experimental result shows that our model gives 82 % accuracy rate for BRAINIX data set and 91% classification accuracy for texture surfaces dataset. The minimum accuracy rate is 82%. As everyday, new feature extraction techniques are evolving, we trust that in the upcoming days, image classification will be much more accurate. The feature extraction process will be much easier in the upcoming days.

## 5.2 Future work

The use of parallel computing with the GPU can significantly accelerate the implementation of the program as more GPU are coming time to time and the architecture is improving. We can hope the next generation GPU architecture will work with better accuracy requiring less time which will lead us to much easier feature extraction process. Several parallel processing techniques have been extensively applied to many application field because of the manifestation of multi-core CPU and GPU. Parallel processing technique for real time feature extraction using our proposed method can bring a significant change in both run time and accuracy.

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