An Entropy Maximization based technique for Progressive Transmission of MRI Images

Arunava De, Dr. Anup Kumar Bhattacharjee, Dr. Chandan Kumar Chanda, Dr. Bansibadan Maji

National Institute of Technology, Durgapur, India

Summary
We have devised a way of segmentation and progressive transmission of MRI images. Entropy maximization using Particle Swarm Algorithm (PSO) is used to get the Region of Interest (ROI). The ROI is de-noised using Multi-Wavelet Analysis. Soft Thresholding together with Stationary Wavelet is used for de-noising purpose. Varying percentages of Discrete Cosine Transform Coefficients are used for the purpose of progressive transmission. K-Means clustering is used for analysis of the MRI.

Keywords
Region of Interest,Discrete Cosine Transform, Particle Swarm Optimization,Computed Tomography, Magnetic Resonance Imaging, Within-class variance, Entropy, Intensity contrast, Progressive Transmission, Multi-resolution Wavelet Analysis,Stationary Wavelet Transform,Soft Thresholding

1. Introduction

Thresholding is a one of the very important technique for image segmentation. Bi-modal image has a single object and background as opposed to multimodal images where there are multiple objects and background. A pictorial depiction of the bi-modal and multi-modal image histogram is given in Figure 1 and Figure 2.The bi-modal image histogram has two peaks and a valley in between whereas multi-modal image has a number of peaks and valleys.

Valley detection and criteria optimization [2,3] are one of the many thresholding approaches that are already defined. Minimum error thresholding method (MinError) assumes the normal distribution of object and background [4,5]. Reference [6] estimated the parameters of normal distribution from a truncated normal distribution corresponding to object and background. Reference [7] was the first to propose a thresholding method based on maximum entropy principle whereas [8] employed cross entropy for threshold selection. Reference [9] applied fuzzy c-partition to gray level images and maximized fuzzy entropy to select the threshold. Reference [10] introduced an energy criterion formulated by intensity-based class uncertainty and region homogeneity. The threshold is selected by minimizing the energy. Reference [11] applied the idea of maximizing the between class variance into histogram-based thresholding. The method shows satisfactory results in various applications. However, it tends to split the larger part when the sizes of object and background are unequal [12]. Reference [6] pointed out that the separation of object and background cannot generally be determined uniquely by the image histogram. Prior knowledge about the relation and properties of object and background can be helpful to improve the performance of thresholding methods. Reference [13] took advantage of the knowledge about the range of background proportion to the ROI to confine the range of threshold selection and achieved reliable results in segmenting magnetic resonance (MR) and computed tomography (CT) images of the human brain.

Reference [1] demonstrated that threshold can be obtained by optimizing the weighted sum of the within-class variance and the intensity contrast. Reference [16] found that using Entropy maximization using PSO algorithm gives better results in comparison with other methods [14].

Reference [15] proposed a method of progressive transmission of MRI image. Reference [16] demonstrated that entropy maximization using Particle swarm algorithm can be used to segment a diseased area of a MRI from a non diseased part. We propose a novel method of segmentation, de-noising using Stationary Wavelet Transform and progressive transmission of segmented diseased MRI images.

The paper proposes a scheme for detection of diseased lesions and progressive transmission of MRI images. Here in this paper we deal with multi-modal MRI images. Our goal is to separate the diseased part from the non diseased part of an MRI image and then we propose a way to perform progressive transmission of the segmented image. In our technique we segregate the image based on levels of intensity, because diseased portion of the MRI image will have a different intensity value with that of a non diseased multimodal MRI image. We perform entropy maximization using PSO algorithm to get a threshold value which segregates the diseased cells from non diseased cells of the MRI image. This gets us the region of interest (ROI). We

Manuscript received April 5, 2011
Manuscript revised April 20, 2011

perform de-noising of the ROI using multi-resolution wavelet analysis and get the final segmented MRI image using the variable mask.
We perform DCT of the already segmented MRI image and then use varying percentages of the DCT coefficients to perform progressive transmission of the MRI image. k-means clustering is used for analysis of the transmitted image.
This paper is organized as follows-next section deals with the process of data acquisition, section III deals with the proposed algorithm, section IV deals with results and discussions, section V is the conclusion and the last section is for the references.

2. MRI Data acquisition and roi

We have taken a set of slices of human brain of patients for testing purposes. We have tested our method in a number of patients. The patients include those who are currently undergoing chemotherapy and also those who are cured of the brain lesions.
We have acquired a set of 2-D slices of human brain of patients for testing purposes. The images are viewed using centricity dicom viewer provided by GE Medical. Different MRI views are as follows FSE Axial T2, AxFlairFast, O-Ax T1 SE S. All the examinations were done on the same 1.5-T MRI imaging device. The thickness of each slice is 5.0 mm and 1.5 mm gap between two slices.

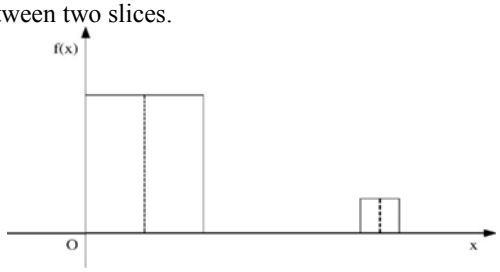

Figure 1. The histogram of uniformly distributed background and object

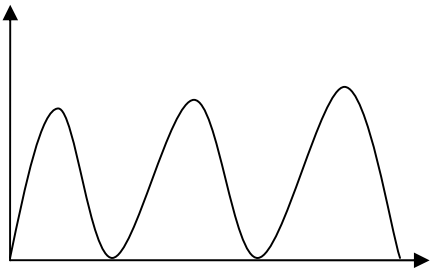

Figure 2. The histogram of a background and object multimodal image

3. Proposed algorithm

3.1 Previous Work Done on Bi-ModalImage

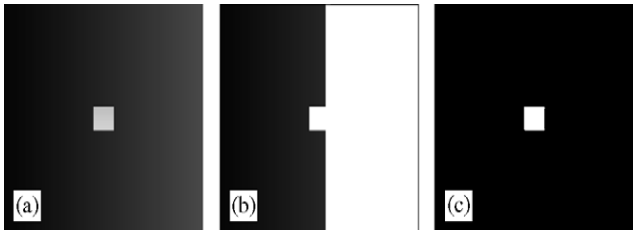

Figure 3. a) Original Image b) Segmentation using Otsu method c)Segmentation using Yu Qiao method

Reference [11] presents a non-parametric and unsupervised method of automatic threshold selection for segmentation of image. A optimal threshold is selected by the discriminant criteria which tries to maximize the separability of the resultant classes of the gray level in the image. The zeroth and first-order cumulative moments of the gray level histogram is utilized making the procedure very simple.
Fig. 3 is a synthetic image which contains a white rectangular box in a black background. There is a smooth variation of intensities from the object and background. The Otsu method misses the valley and sets the optimum threshold somewhere near the middle of the background. Whereas Yu Qiao method was able to properly segment the synthetic image.
Reference [1] proposed a criteria that combines the within-class variance and the intensity contrast,

$$J(\lambda,T)=(1-\lambda)\sigma_w(T)-\lambda\left|m_o(T)-m_b(T)\right| \quad (1)$$

where $m_o(T)$ and $m_b(T)$ are mean intensities of the object and background, respectively. $\sigma_w(T)$ is the square root of within-class variance,

$$\sigma^2{}_w(T)=P_b(T)\sigma_b{}^2(T)+P_o(T)\sigma_o{}^2(T) \quad (2)$$

where $P_b(T)$ and $Po(T)$ are probabilities of the background and object, $\sigma_b^2(T)$ and $\sigma_o^2(T)$ are corresponding variances of the background and object, respectively (see Ref. [11] for their calculation). In this criterion, the within-class variance measures the intensity homogeneity within the object and background while intensity contrast captures the intensity difference between them. The parameter λ is a weight that balances their contributions. When $\lambda = 0$, the criterion degenerates to the within-class variance. If $\lambda = 1$, thresholding is determined only by the intensity contrast, which may yield the threshold at the largest intensity of the image. Therefore, the weight should be in the range of [0, 1]. The optimum threshold T^* is selected by minimizing the criterion.

$$J(\lambda, T^*) = \min_T J(\lambda, T) \tag{3}$$

Eq. (3) actually tries to decrease the within-class variance and increase the intensity contrast simultaneously. In this way, the intensity contrast becomes an explicit factor for determining the optimum threshold.

3.2 Proposed Criteria of Segmentation for Multimodal Images

One of the basic disadvantages of the above system is that it cannot segregate an image based on the intensity levels in case of Multimodal images (MRI images). MRI image has a multimodal histogram (Fig. 2) i.e it may have number of valleys instead of a single valley in case of bimodal histogram.
We use the Entropy maximization technique and the corresponding optimization of the function H (Shanon Entropy) for the threshold gray level range at which the diseased cells differ from that of non diseased cells. Now the threshold value of segregation is than modified to get a exact value at which the diseased and non-diseased cells are completely segregated.

1) Entropy maximization using PSO Algorithm to get the ROI:
First we compute the normalized histogram h(n) for a gray image f(x,y).

$$P_n = h(n) = f_n / N, n = 0,1,2,...255 \tag{4}$$

Where f_n is the observed frequency of gray level *n* (or fn is the number of pixel that having gray level n) and *N* is the total number of pixels in the picture. For multimodal image we want to divide the total image into *(k+1)* number of homogeneous zones and for that we consider the threshold gray levels at $t_1, t_2, t_3, ...t_k$.
Shanon Entropy is defined as

$$H = -\sum_{n=0}^{t_1} P_{1n} \ln P_{1n} - \sum_{n=t_1+1}^{t_2} P_{2n} \ln P_{2n} .... - \sum_{n=t_n+1}^{255} P_{kn} \ln P_{kn} \tag{5}$$

Where

$$P_{1n} = P_n / \sum_{n=0}^{t_1} P_n \quad \text{for } 0 \le n \le t_1$$

$$P_{2n} = P_n / \sum_{n=t_1+1}^{t_2} P_n \quad \text{for } t_1 < n \le t_2.$$

$$P_{kn} = P_n / \sum_{n=t_k+1}^{255} P_n \quad \text{for } t_k < n \le 255$$

We have obtained the function *H* for the threshold gray level t_1 to t_k using PSO (Particle Swarm optimization) algorithm. Now we apply this expert knowledge that the gray level of diseased zone of a MRI image vary from range say *Tx* to *Ty*. Using this expert knowledge, we apply our concept of variable low pass filter mask after optimizing the threshold range using PSO which is explained in subsequent section.

2) Optimization using PSO algorithm:
We optimize the basis functions obtained using Entropy maximization technique using the concept of PSO algorithm. PSO algorithm as applied to our technique:
To maximize function $f(X)$ with
$X^{(l)} \le X \le X^{(u)}$
Where $X^{(l)}$ and $X^{(u)}$ denote the lower and upper bounds on X. PSO works as follows:

① Assume the size of the swarm (number of particles) is N.

② Generate the initial position of X in the range $X^{(l)}$ and $X^{(u)}$ randomly as $X_1, X_2 .....X_N$.

③ Velocity is assigned for each particle as $V_1, V_2 .....V_N$.

④ Evaluate objective function values corresponding to the particles. Initially all the particle velocities are assumed to be zero and set the iteration number as i=1.

⑤ In i^{th} iteration find the following two parameters.

Calculate the historical best value of $X_j(i)$ called $P_{best,j}$. Also find G_{best}, the highest value of objective function encountered in all the previous iterations by any of the N particles.

⑥ Update the velocity as follows

$$V_j(i) = \theta V_j(i-1) + c_1 r_1 [P_{best,j} - X_j(i-1) + c_2 r_2 [G_{best} - X_j(i-1)]; j = 1,2....N. \tag{6}$$

⑦ Update the position of the particle as

$$X_j(i) = X_j(i-1) + V_j(i); j = 1,2...N \tag{7}$$

⑧ Check the convergence of the current solution . If the convergence criteria is not satisfied then repeat steps 5, 6,7

The PSO algorithm is used for optimizing the initial value of threshold to be used for segmenting the MRI image using variable mask.

3.3 Multi-resolution Wavelet De-Noising of ROI using Stationary Wavelet and Soft Thresholding :

In signal analysis we can perform several functions to translate the signal into different forms so that it becomes suitable for different applications. The Fourier Transform converts a signal from time versus amplitude to frequency versus amplitude, that is it transforms a time domain signal to frequency domain signal. The resultant transform is useful for many applications but it is not based in time. Also the Fourier transform for a stationary and non-stationary signal is the same. Thus we have to keep resolution across the entire signal and still be based in time. This led to the use of Wavelet transform which has frequency and time domain information.

Discrete Wavelet Transform (DWT) is not a time-invariant Transform. This means that even with periodic signal extension, the DWT of a translated version of a signal Y is not in general the translated version of the DWT of Y. The Stationary Wavelet Transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of Discrete Wavelet Transform (DWT). Translation –invariance is achieved by removing the down-samplers and up-samplers in the DWT and up-sampling the filter coefficients by a factor of 2(j-1) in the jth level of the algorithm. The main application of SWT is de-noising. There is however a restriction that SWT is defined only for signals of length divisible by 2J, where J is the maximum decomposition level. Fig.4 gives the filter bank of Stationary Wavelet Transform.

We have used a general wavelet based approach [19] for de-noising the image. We have used Stationary Wavelet Transform (SWT) and Inverse Stationary Wavelet Transform for the de-noising purpose. We have done level 2 decomposition of the ROI of diseased MRI image. We have used Daubechies wavelets because they have good compression property for wavelet coefficients but not for approximation coefficients. Daubechies wavelets are fully parameterized and have straightforward procedure for calculation of their analysis filters.

The threshold selected for Soft thresholding for detail coefficients is 40.87. The output of de-noising the ROI of the diseased MRI image is shown in Fig.5(c). Using a variable mask we get the final segmented MRI image as explained in the next sub-section.

3.4Concept of variable mask:

We start with a 3×3 mask. All the pixel positions having a value more than the threshold value obtained using Entropy maximization forms the ROI. The mask is moved over the de-noised ROI, if the neighborhood pixels display a similar value we increase the size of the mask. The mask is grown in all the four directions depending on the similarities of the pixel values. If the neighborhood pixels have different value then we again start afresh in the new region of the ROI. After execution of this procedure we get a segregated image containing the diseased cells of the MRI image. The result of this step is shown in Fig.5(d).

3.5 Progressive Transmission of MRI images using DCT coefficients

For large amounts of data and in our case 2-D MRI data poses problems in network transmissions. During progressive viewing at the recipient node if the evolving transmissions indicate that the object is desirable than we continue transmission else drop the transmission.

We take a set of 20 MRI images in the Axial T2 view which mainly gives the pathology of the disease. Each slice is having a resolution of 512×512. We denote this digital object as $\{(y_s, N_S)\}_{s=0}^{19}$, where $y_0 < y_1 < y_2 < \ldots\ldots < y_{20}$ provide ordering of the slices, from top to bottom of the head and N_s are 512×512 matrices.

A very simple scheme for progressive transmission at the transmitter end can be taking each slice one at a time and get the segmented MRI image using Entropy maximization using PSO algorithm and variable mask as discussed in sub-section B-1,2,3,4 of section III. After getting the segmented image of each slice of MRI image we perform Discrete Cosine Transform[20] of the segmented MRI slice. The original slice and segmented MRI image slice are displayed in Figure 5(a) and Figure 5(d).

After getting the DCT of segmented diseased MRI slice we perform inverse DCT of the segmented MRI taking 10 % to 100% of the coefficients may be in steps of 10. We use *k-means* clustering to get the clustered view of the each of the images obtained. Progressive transmission of the MRI slice with 30%, 40% and 50% of the coefficients are displayed in Figure 6 a),b),c). The images obtained are then transmitted progressively for detection of anomalies at the receiver's end.

3.6Analysis and detection of progressively rendered diseased MRI images using k-means clustering technique.

Clustering Analysis is a fundamental but important tool in statistical data analysis. Clustering techniques have been widely applied in a variety of scientific areas as pattern recognition, information retrieval, microbiology analysis, and so forth.

k-means clustering [17],[18] has k number of cluster centers. K-means clustering aims to partition *N* inputs (called data points) x_1, x_2, $x_3 \ldots x_n$ into k clusters by assigning an input x_t

into the j^{th} cluster if the indicator function $I(j/x_t) = 1$ holds with
$I(j/x_t)$= { 1 if j=argmin$_{1\le r\le k}$ || $x_t - m_r$ ||^2 ;{ 0 otherwise
(8)

Here, $m_1, m_2, ..m_k$ are called seed points that can be learned in an adaptive way as follows:
Step 1: Pre-assign the number k of clusters, and initialize the seed points $\{m_j\}_{j=1}^{k}$.
Step 2: Given an input x_t, calculate $I(j/x_t)$ by (8).
Step 3: Only update the winning seed point m_w, i.e., $I(w/x_t)$=1, by

$$m_w^{new} = m_w^{old} + \eta(x_t - m_w^{old}), \qquad (9)$$

Where η is a small positive learning rate.
The above step 2 and step 3 are repeatedly implemented for each input until all seed points converge.
We perform *k-means* clustering on the images that are obtained by varying the percentage of DCT coefficients. The result of the clustering helps us to analyze the images. The clustering results in predominantly two clusters namely diseased cells and the background. The result of the clustering is shown in Fig.6(a),(b),(c).

4. Results and Discussions

In the case Figure. 5(a), we take ten particles for each of three dimensional spaces taken, where each dimension of space represents a threshold value. Using PSO we get three threshold values 20,100, 157. Using expert knowledge we observe that diseased cells of MRI image lie above the threshold value of 157 using θ =0.9 to 0.4, c_1=1 and c_2=2.
Using the threshold value we get the region of interest which contains all diseased cells along with small number of non diseased cells, the results of the process is shown in Figure 5(b).
We de-noise the ROI using Multi-resolution Wavelet Analysis. We use Stationary Wavelet Transform and the method of Soft thresholding to get the de-noised ROI. The threshold used for Soft thresholding is 40.87. The results of de-noising are shown in Figure 5(c).
The variable mask is applied in a region growing manner on the ROI to get the final segmented MRI image as shown in Figure 5(d).
Discrete Cosine transform of Figure 5(d) is carried out. The results of k-means clustering after performing Inverse Discrete Cosine Transform by taking 30%, 40%, 50% of the DCT coefficients for the purpose of progressive transmission are displayed in Figure 6. The results clearly show that even with 30% coefficients the lesions are more or less visually clear as shown in Figure 5(a). As the percentage of coefficients increase the images become progressively clearer. The method of progressive transmission of diseased MRI images proposed here is effective for detection of diseases. Here we have proposed that k-means algorithm can be used to analyze the progressively transmitted images.

5. conclusion

The proposed method is very useful for progressive transmission of diseased MRI images. The analysis is done using k-means algorithm but other methods of analysis can be devised. The proposed scheme is for 2D MRI slices. The proposed method can be suitably modified for 3D progressive image transmission of diseased MRI images by retaining internal data or features.

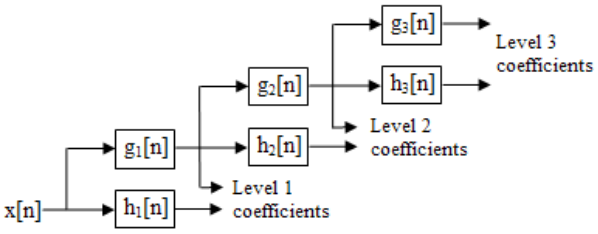

Figure 4. SWT filter bank

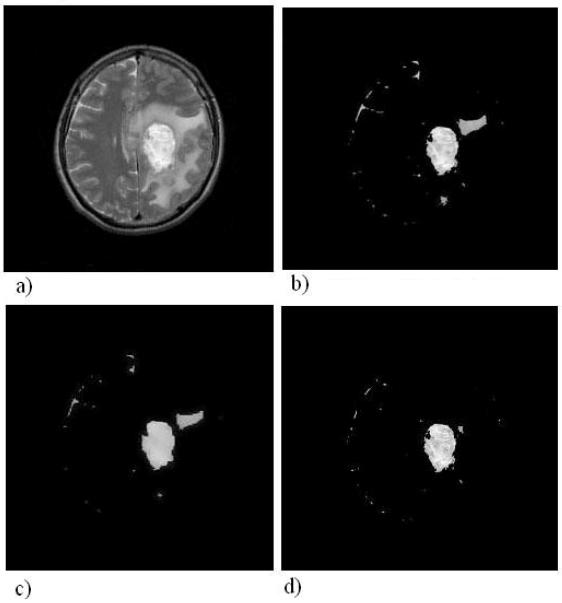

Figure 5. Diseased MRI Image b) ROI using PSO Algorithm c) De-noised Image using SWT and Soft Thresholding d) Segmented Image using variable mask.

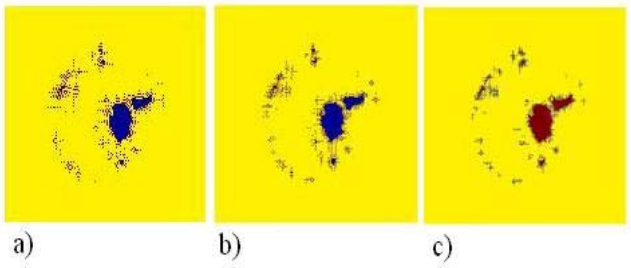

Figure 6. Progressive transmission of Figure.5(d). with a) 30 % coefficients b) 40% coefficients c) 50% coefficients

References

[1] Y. Qiao, Q. Hu, G. Qian, S. Luo, and W. L. Nowinski, "Thresholding based on variance and intensity contrast," Pattern Recognition, vol. 40, pp. 596 – 608, 2007.

[2] J.M.S. Prewitt, and M.L. Mendelsohn, "The analysis of cell images," Ann. N. Y. Acad. Sci. vol. 128, no. 3, pp. 1035–1053, 1966.

[3] J.S. Weszka, and A. Rosenfeld, "Histogram modification for threshold selection," IEEE Transactions on Systems, Man and Cybernetics, vol. 9, no. 1, pp. 38–52, 1979.

[4] J. Kittler, and J. Illingworth, "Minimum error thresholding," Pattern Recognition, vol. 19, no. 1, pp. 41–47, 1986.

[5] S. Cho, R. Haralick and S. Yi, "Improvement of Kittler and Illingworth's minimum error thresholding", Pattern Recognition, vol . 22,no .5,pp. 609–617,1989.

[6] J.S. Lee and M.C.K. Yang, "Threshold selection using estimates from truncated normal distribution", IEEE Trans. Syst. Man Cybern.,vol. 19,no. 2,pp. 422– 429, 1989.

[7] T. Pun, "Entropic thresholding: a new approach", CVGIP: Graphical Models Image Process.,vol. 16,pp. 210– 239,1981.

[8] C.H. Li and C.K. Lee, "Minimum cross entropy thresholding", Pattern Recognition , vol. 26,no. 4 ,pp. 617– 625,1993.

[9] H.D. Cheng, J.R. Chen and J.G. Li, "Threshold selection based on fuzzy c-partition entropy approach", Pattern Recognition ,vol . 31,no . 7, pp . 857–870,1998.

[10] P.K. Saha and J.K. Udupa, "Optimum image thresholding via class uncertainty and region homogeneity", IEEE Trans. Pattern Anal. Mach. Intell. ,vol . 23, no .7,pp . 689–706,2001.

[11] N. Otsu, "A thresholding selection method from gray-level histograms", IEEE Trans. Syst. Man Cybern, vol .9,no . 1,pp .62–66,1979.

[12] J. Kittler and J. Illingworth, "On threshold selection using clustering criteria", IEEE Trans. Syst. Man Cybern., vol . 15, no . 5, pp . 652–655,1985.

[13] Q. Hu,Z. Hou and W.L. Nowinski, "Supervised range-constrained thresholding", IEEE Trans. Image Process,vol .15,no . 1,pp . 228–240,2006.

[14] Y.Kabir, M.Dojat, B.Scherrer, F.Forbes, C.Garbay, "Multimodal MRI Segmentatation of Ischemic Stroke lesions" , Proceedings of the 29 thAnnual International Conference of the IEEE EMBS, Cite Internationale, Lyon France,August 23-26, 2007.

[15] Zhu, H., Brown, R.A., Villanueva, R.J., Villanueva-Oller, J., Lauzon, M.L., Mitchell, J.R. and Law, A.G., Progressive imaging: S-transform order. ANZIAM J. v45 iE. C1002-C1016.

[16] Arunava De, Rajib Lochan Das, Anup Kumar Bhattacharjee, Deepak Sharma," Masking based Segmentation of diseased MRI images", International Conference on Information Science and Applications, ICISA 2010 proceedings, IEEE Seoul chapter, Seoul,Korea,pp.230-236, 978-1-4244-5941-4/10

[17] MacQueen, J.B., "Some methods for classification and analysis of multivariate observations", In: Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability, University of California Press, Berkeley, CA,pp.281–297,1967.

[18] R.O. Duda, P. E. Hart, D .G. Stork ,"Pattern Classification",pp.526-528, Second Edition, John Wiley and Sons, 2004.

[19] R.C. Gonzalez, R.E. Woods, "Digital Image Processing", pp.392, 472-477, Second Edition, Prentice Hall India, 2002.

[20] K.R. Rao and P. Yip, Discrete Cosine Transform: Algorithms, Advantages, Applications. New York:Academic, 1990