International Journal of Computer Sciences and Engineering Open Access
Research Volume-6, Issue-6 E-ISSN: 2347-2693

Attribute Selection for the Early Diagnosis of Alzheimer's Disease from Magnetic Resonance Images

C.S. Sandeep[1*], A. Sukesh Kumar[1]

[1*]Electronics and Communication, College of Engineering, University of Kerala,Trivandrum, India

e-mail: sandeepnta2@gmail.com, drsukeshkumar@yahoo.in

[*]*Corresponding Author: sandeepnta2@gmail.com, Tel.: +919446084508*

Available online at: www.ijcseonline.org

Accepted: 13/Jun/2018, Published: 30/Jun/2018

Abstract— Alzheimer's disease (AD), also known as Senile Dementia of the Alzheimer Type (SDAT) or simply Alzheimer's is the most common form of dementia. The AD is a slowly progressive disease of the brain that is characterized by impairment of memory and eventually by disturbances in reasoning, planning, language, and perception. Many scientists believe that Alzheimer's disease results from an increase in the production or accumulation of a specific protein called beta-amyloid protein in the brain that leads to nerve cell death. Conventional clinical decision-making systems are more manual in nature and ultimate conclusion in terms of exact diagnosis is remote. In this case, the employment of advanced Biomedical Engineering Technology will definitely helpful for making a diagnosis. Profiling of human body parameter using computers can be utilized for the early diagnosis of Alzheimer's disease. There are a lot of tests and imaging modalities to be performed for an effective diagnosis of the disease. In this paper, we have focused on MRI imaging for making an expert system for the diagnosis of the AD. For this purpose, we have used Discrete Wavelet Transform for the segmentation of MRI images. After segmentation, some of the attributes extracted using histogram, gradient, SURF, and Gabor has been done. Finally, we have selected some attributes based on the criteria of early diagnosis through MRI brain images.

Keywords—Alzheimer's Disease, MRI, Discrete Wavelet Transform, histogram, gradient, SURF, Gabor

I. Introduction

In the past several decades, investigators have learned much about what happens in the brain when people have a neurodegenerative disease such as Parkinson's disease, AD, or other dementia. Their findings also have revealed much about what happens during healthy aging. Researchers are investigating a number of changes related to healthy aging in hopes of learning more about this process, so they can fill gaps in our knowledge about the early stages of AD [1]. As a person gets older, changes occur in all parts of the body, including the brain. Certain parts of the brain shrink especially the prefrontal cortex (an area at the front of the frontal lobe), and the hippocampus. Both areas are important to learning, memory, planning, and other complex mental activities. Changes in neurons and neurotransmitters affect communication between neurons. In certain brain regions, communication between neurons can be reduced because white matter (myelin-covered axons) is degraded or lost. Changes in the brain's blood vessels occur. Blood flow can be reduced because arteries narrow, and less growth of new capillaries occurs. In some people, structures called plaques, and tangles develop outside of, and inside neurons, respectively, although in much smaller amounts than in AD [2]. The AD is the sixth-leading causes of death among various diseases and is 70% widespread in all cases of dementia [3]. The development of AD can be placed into four stages. The first stage is called Mild Cognitive Impairment (MCI) that does not make prominent changes in day to day living. After the first stage, the second, and third stages of the disease are called Mild, and Moderate AD [4]. These stages describe the distinctive nature by a rise in cognitive shortfall and reduction in independence. The fourth stage is called Severe AD in which the affected person almost dependent on caregivers, and an overall decline of personality [5, 6]. The brains of people with AD have an abundance of two abnormal structures are amyloid plaques, and neurofibrillary tangles, the most widely known neuropathological hallmarks of AD [7, 8]. Senile plaques present outside the neuron, appear as spherical bodies bearing dilated, and tortuous neuritic processes around an amyloid beta core which contains some abnormal proteins like amyloid beta plaques which are derived through the processing of Amyloid Precursor Protein (APP) [9, 10]. Familial causes or genetic reasons involved in disease pathology include mutations on chromosomes 21, 14, and 1. Risk factors for the AD are elder age, small head size, history of head trauma, lower intelligence, and female gender [11].

© 2018, IJCSE All Rights Reserved

The imaging modalities tests that were established for AD are Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET). From the above MRI measure the whole brain volumes, medial temporal lobe structures, and ventricular volumes. Therefore, MRI can be helpful in differentiating between MCI and AD [11]. PET is an imaging modality that uses biochemical ways of getting images rather than structural information. PET technology includes the detection of photons which records the levels of radioactivity beginning from given points in time and space. Positron emitting radioisotopes are used to generate the radioactivity [12]. PET scan measures different compounds in the brain especially the fluorodeoxyglucose (FDG) that can compete with glucose for metabolism and absorption in neurons. There are some recent advances in technology that can not only detect AD, but it can explain the symptoms and how the disease works. For an effective and early diagnosis of AD, a population-based study is necessary and required, which gives an idea about the various tests involved in determining AD. In this paper we have concentrated on MRI images for the early diagnosis of AD. After segmentation attribute extraction and attribute selection is done for the early diagnosis of AD.

The paper is organized as follows, Section I contain the introduction of the research work, Section II contains the related work of the previously published paper, Section III contain the methodology, Discrete Wavelet Transform is described, Section IV deals with the attribute extraction, Section V deals with the attribute selection, Section VI describes results and discussion, and Section VII concludes research work with future directions.

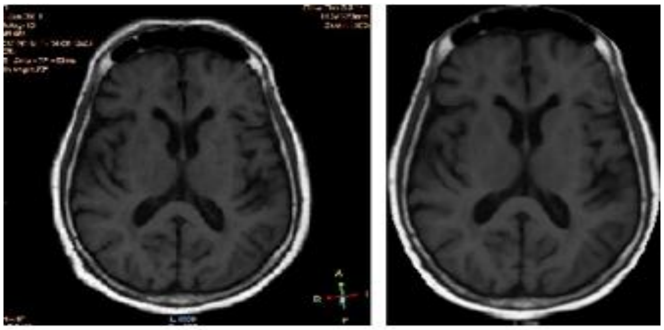
II. Related Work

Some of the previous works related to this article are as follows. There are different ways for the segmentation of images in the artificial intelligence field. Most prominent and popular of them are fuzzy logic and artificial neural network approaches for segmentation of medical images [13, 14]. Segmentation of Optical Coherence Tomography images using Wavelet Networks was described for the early diagnosis of Alzheimer's disease [15-17]. Techniques and comparative analysis of medical image segmentation were proposed using neural network systems [18]. Analysis of MRI and OCT Images for the Early Diagnosis of Alzheimer's Disease was described using Wavelet Networks [19]. Wavelet neural network approach for calibration model building based on gasoline near infrared (NIR) spectra was also described [19].

III. Methodology

Apart from above another promising computational intelligence method that has been widely used for various applications in different areas is DWT. A wavelet can be called as a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. A family of wavelet scan is formed from a function, called "mother wavelet," which is confined in a finite interval. "Daughter wavelets" are then formed by shifting and scaling of the mother wavelet. Wavelets are mainly used for compressing image data from a larger one. Wavelet takes full advantage of the characteristics of denoising, background reduction, and recovery of the characteristic information and Neural Network capacity of universal approximation [19-22]. For this reason, it has a great ability to be used in many different applications [23, 24]. For instance, in image processing, DWT have overcome many of the limitations in other intelligent methods such as Artificial Neural Networks. The main advantage of DWT over similar architectures such as multi-region perceptrons (MLP) and networks of radial basis functions (RBF) is the possibility of optimizing the DWT by means of efficient deterministic construction algorithms [25]. In this paper, a specific DWT for segmentation of MRI images is employed. Wavelet networks are classified into two groups. They are adaptive wavelet networks (AWNs) and discrete DWT [26]. AWN is continuous whereas the DWT is discrete. Due to numerous shortcomings of AWNs like for example, complex calculations, sensitivity to initial values, and the problem of measuring initial values, their application is limited [28]. In a DWT, the outer parameters of the network like the number of wavelets, scale, and shift parameters value are determined. The only inner parameters of the network, weights are specified by algorithms similar to the least squares. These types of networks do not need training. In AWNs, initial values of network parameters including weights of neurons, shifts, and scales of wavelets are selected randomly or using other methods. These parameters are then updated in the training stage by means of techniques such as gradient descent or back propagation (BP). Then, the optimized values of network parameters are calculated. But in this method, the number of wavelets, as well as the scale and shift parameters, can be determined in advance and the only unknown parameters are the weight coefficients which are calculated through methods such as least squares. So in the proposed method, there is no need to specify random initial values for parameters or to use gradient descent, BP, or other iterative methods. Normally, in training stage of an adaptive network, all the parameters change; on contrary, in DWT only, the weights are specified during an on iterative process. Thus, it could be concluded that DWT does not need training procedure. In this paper, we have done the segmentation process with the help of DWT. The figure 1(a) shows original image and 1(b) shows the segmented image.

© 2018, IJCSE All Rights Reserved



(a) (b)

Figure 1: (a) original image (b) segmented image

IV. ATTRIBUTE EXTRACTION

After the segmentation is over, the next step is to extract the attributes of the segmented region. Attribute extraction involves reducing the number of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power; also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples. Attribute extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. In this proposed method, attribute extraction techniques like histogram, entropy, gradient; SURF and Gabor filter is used. They are discussed below.

A. Histogram

The histogram of a digital image is the intensity distribution of that image in a graphical form. It plots every intensity value against the number of pixels in an image. When someone watches an image histogram he will be able to identify the entire intensity distribution at a glimpse. For example, in an 8-bit grayscale digital image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels against those grayscale values. A histogram of a digital image with gray levels in the range *[1, M]* is a discrete function $f(g_k)$, where g_k is the k^{th} gray level, and n_k is the number of pixels in the image having gray level g_k. The normalization of a histogram is done by dividing each of its value by the total number of pixels denoted by n as shown in equation 1[29].

$$p(g_k)=n_k/n \text{ for } k=1,2,..,M \quad (1)$$

where $p(g_k)$ estimates the probability of occurrence of the gray level g_k. Histograms are usually used for computing a binary image $b_{i,j}$ from a given image $f_{i,j}$ so that $i=1,..X$, $j=1,..,Y$ where X,Y describes the size of the image in pixels $(n=X*Y)$. The binarization is usually done by a threshold operation. A suitable value for θ can be found by creating a gray-level histogram. The figure 2 shows the histogram output of the segmented MRI image as shown in equation 2.

$$b_{i,j} = \begin{matrix} 0 & if\ f_{i,j} \le \theta \\ 1 & otherwise \end{matrix} \quad (2)$$

The mean of the image is calculated as in equation 3.

$$\mu = \sum_{k=1}^{M} g_k P_k \quad (3)$$

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. The entropy of a histogram (image) is calculated as in equation 4.

$$\mu = \sum_{k=1}^{M} P_k log_2 P_k \quad (4)$$

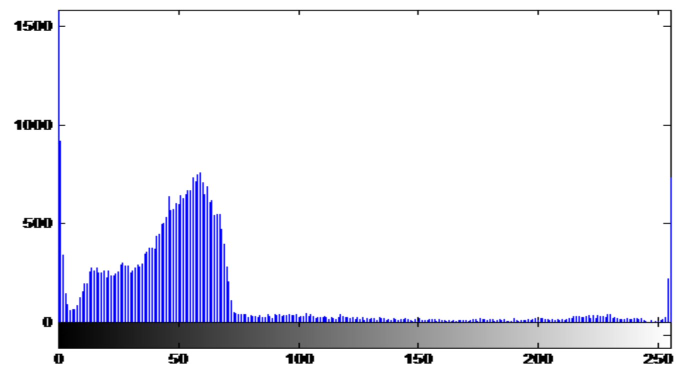


Figure 2: Histogram output of segmented MRI image

B. Gradient

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Mathematically, the gradient of a two-variable function (here the image intensity function) at each image point is a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction [30]. The gradient of an image is given by the formula as in as equation 5.

$$grad.f = [g_x\ g_y]^T = [\frac{d_f}{d_x}\ \ \frac{d_f}{d_{yx}}]^T \ldots\ldots(5)$$

where *df/dx* is the gradient in *x* direction and *df/dy* is the gradient in *y* direction. The gradient attributes are shown in figure 3. The gradient direction can be calculated by the formula as in equation 6.

$$\theta = tan^{-1}[g_x\ g_y]^T \ldots\ldots\ldots(6)$$

© 2018, IJCSE All Rights Reserved

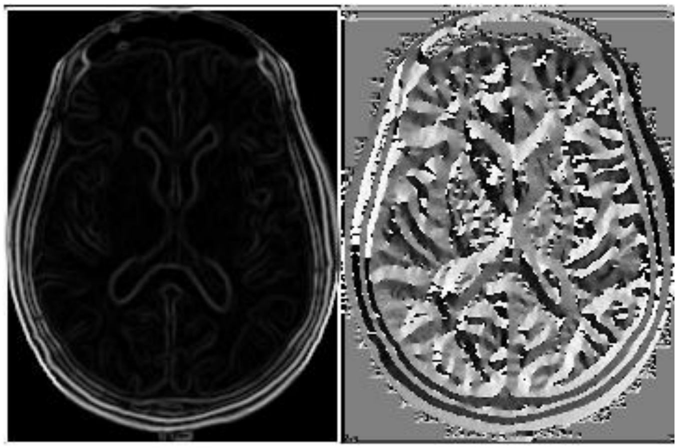


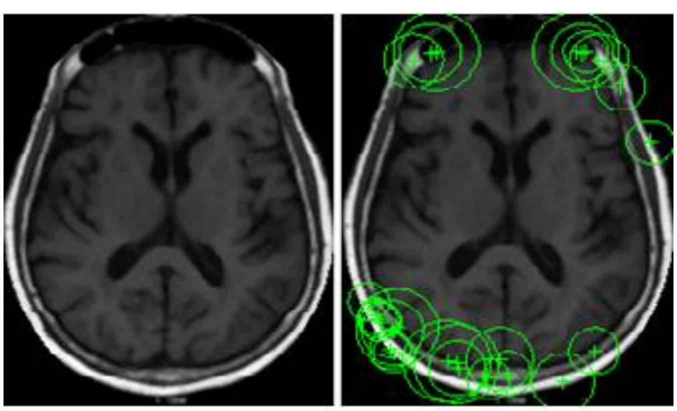
Figure 3: Gradient attributes

C. SURF

The SURF algorithm is based on the same principles and steps as SIFT, but details in each step are different. The algorithm has three main parts: interest point detection, local neighborhood description and matching. SURF uses square-shaped filters as an approximation of Gaussian smoothing. (The SIFT approach uses cascaded filters to detect scale-invariant characteristic points, where the difference of Gaussians (DoG) is calculated on rescaled images progressively.) Filtering the image with a square is much faster if the integral image is used as in equation 7 [31]:

$$S(x,y = \sum_{i=o}^{x}\sum_{j=0}^{y} I(i,j) \ldots\ldots\ldots..(7)$$

The sum of the original image within a rectangle can be evaluated quickly using the integral image, requiring evaluations at the rectangle's four corners. The extracted surf attributes are shown in figure 4



(a) (b)

Figure 4: (a) Segmented image (b) SURF attributes

D. Gabor Filter

A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful attributes from an image. In the discrete domain, two-dimensional Gabor filters are given by equations 8 and 9 [32],

$$G_c[i,j] = Be^{-\frac{(i^2+j^2)}{2\sigma^2}}\cos\big(\omega(icos\theta + jsin\theta)\big) \ldots\ldots..(8)$$

$$G_s[i,j] = Ce^{-\frac{(i^2+j^2)}{2\sigma^2}}\sin\big(\omega(icos\theta + jsin\theta)\big) \ldots\ldots\ldots(9)$$

where B and C are normalizing factors to be determined. 2-D Gabor filters have rich applications in image especially in attribute extraction for texture analysis and segmentation processing which is shown in figure 5.

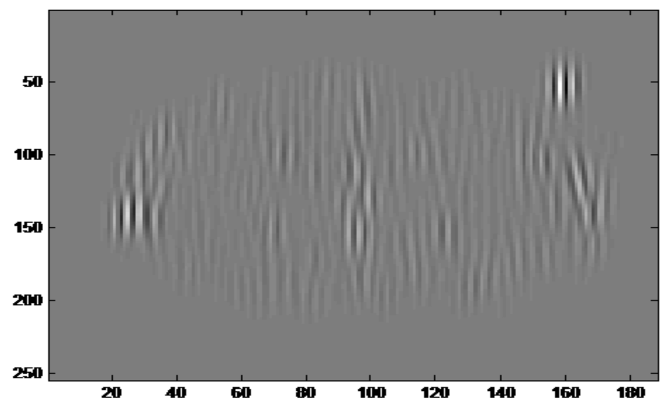


Figure 5: Gabor attributes of segmented MRI image

V. ATTRIBUTE SELECTION

After the attribute extraction step, next is the attribute selection in which we can select the required attributes. In this paper we have use the different attributes like histogram, entropy gradient, SURF and Gabor. For getting better accuracy, specificity and sensitivity we have selected all the attributes. With an effective combination of all the attributes selected will help for the diagnosis of AD.

VI. RESULTS AND DISCUSSION

The database includes different MRI images taken from Siemens magnetom essenza 1.5tesla under the same environmental conditions. All of these images taken from patients suspected to AD. It is worth noting that the database images employed in this paper were free of any noise or artifacts. In case of noisy images (images which are not of desired quality or the results of segmentation are not satisfactory), or necessity of elimination of the hairs, a pre-processing stage be used. Among the images selected for segmentation using the proposed method, best images were used for building the network In our experiments, 10–12 wavelets are enough to achieve good results, since extracting the attributes of brain is the most essential part of diagnosing Alzheimer's Disease, extracting the brain region is a vital

© 2018, IJCSE All Rights Reserved

task. For this, after segmentation with a DWT and according to the proposed, the space between two shapes is filled, extra parts are eliminated, and the noise is removed. Then, the exact boundary of brain region is extracted. This is done with the help of appropriate attributes selected during the attribute extraction process. As mentioned before, segmentation is the most important and critical stage of the three stages of automatic diagnosis of brain region which has a very significant role in the final outcome. Because of this reason, the performance of this state should be examined by means of appropriate criteria. Our method is quite simple and considering the satisfactory results of this study, it is very applicable for detecting AD. From the existing work we get a segmented image with ROI processing, the attribute extraction and attribute selection has been done. In the future works classification of MRI images can be done. From images database, a number of images are randomly chosen for formation of DWT. At first the values of R, G, and B matrices of each color MRI image are mapped into [0, 1] range by performing normalization process. DWT is formed with three inputs, a hidden region, and an output. In order to form the DWT, the values of three color matrices are considered as network inputs. These matrices are related to the best chosen images from the selected images for segmentation. From these images, some pixels are selected randomly. In this way, the DWT is formed. After that, the value of the three matrices R, G, and B for each pixel are considered as DWT inputs, and the output of DWT is a binary image that shows the segmented of original image. After the segmentation is over, attribute extraction and attribute selection has done. The output of each attributes extracted is shown on the attribute extraction section.

VII. CONCLUSION and Future Scope

In this study a new approach for the segmentation of MRI using DWT is explained. This method can provide better accuracy, sensitivity and specificity than the previous related works. Some of the attributes extracted are done by using histogram, gradient, SURF, and Gabor. This method can be used for making an expert system for the early diagnosis of AD. In this work, segmentation using DWT, the attributes extracted and selected according to the criteria. In the future work, image classification can be done to provide an expert system for diagnosing AD.

.

ACKNOWLEDGMENT

We are thankful to Dr. K.Mahadevan, Dr.Manoj P, Dr.Praveen Panicker and Sree Gokulam Medical College and Research Foundation, Trivandrum, Kerala, India for their support in this research work.

REFERENCES

[1] Sandeep C S, Sukesh Kumar A, "*A Review on the Early Prediction of Alzheimer's Disease (AD) through Different Tests, Techniques and Databases"*, AMSE JOURNALS Series: Modelling C, Vol. 76, Issue.1; pp.1-22, 2015.

[2] Harvey, R.A., P.C. Champe, B.D. Fisher, *Lippincott's Illustrated Reviews*: *Microbiology.* 2nd Edn., Lippincott Williams and Wilkins, pp.432, 2006.

[3] Sandeep C S, Sukesh Kumar A, Susanth M J, "*The Online Datasets Used to Classify the Different Stages for the Early Prediction of Alzheimer's Disease (AD)* ",International Journal of Engineering and Advanced Technology, Vol.6, Issue.4, pp.38-45, 2017.

[4] Cummings, J.L., H.V. Vinters, G.M. Cole and Z.S. Khachaturian, "*Alzheimer's disease: etiologies, pathophysiology, cognitive reserve and treatment opportunities*", Neurology, Vol.51. pp.2-17, 1998.

[5] Sandeep C S, Sukesh Kumar A, Susanth M J "*The Early Diagnosis of Alzheimer Disease (AD) Using CAMD, TREAD and NAAC Databases"* International Journal for Science and Advance Research In Technology, Vol.3, Issue.3, pp.366-371, 2017.

[6] Yaari, R. and J. Corey-Bloom, "*Alzheimer's disease: Pathology and pathophysiology*", Semin Neurol. Vol.27, pp.32-41, 2007.

[7] Larson EB, Wang L, Bowen JD, et al. "*Exercise is associated with reduced risk for incident dementia among persons 65 years of age and older*", Ann Intern Med., Vol.144, pp.73-81, 2006.

[8] Mayeux R. "*Epidemiology of neurodegeneration",* Annu Rev Neurosci., Vol.26, pp.81-104, 2003.

[9] Sandeep C S, Sukesh Kumar A ,"*A Psychometric Assessment Method for the Early Prediction of Alzheimer's disease*", International Journal of Scientific & Engineering Research, Vol.8, Issue.3, 2017

[10] Harvey RJ, Skelton-Robinson M, Rossor MN. "*The prevalence and causes of dementia in people under the age of 65 years*", J Neurol Neurosurg Psychiatry, Vol.74, pp.1206-9, 2003.

[11] Chu LW, Tam S, Wong RL, et al. "*Bioavailable testosterone predicts a lower risk of Alzheimer's disease in older men*", J Alzheimers Dis; 21:1335-45, 2010.

[12] Sandeep C S, Sukesh Kumar A, Susanth M J," *Cognitive Examination for the Early Diagnosis of Alzheimer's Disease",* IEEE International Conference on Trends in Electronics and Informatics, 2017

[13] K.-S. Cheng, J.-S. Lin, and C.-W. Mao, "Techniques and comparative analysis of neural network systems and fuzzy systems in medical image segmentation," Fuzzy Theor. Syst. Tech. Appl., Vol.3, pp.973–1008, 1999.

[14] J. Jiang, P. Trundle, and J. Ren, "Medical image analysis with artificial neural networks," Comput.Med. Imag. Graph., Vol. 34, Issue.8, pp. 617–631, 2010.

[15] Sandeep C S, Sukesh Kumar A, K Mahadevan and Manoj P, *"Dimensionality Reduction of Optical Coherence Tomography Images for the Early Diagnosis of Alzheimer's Disease*", American Journal of Electrical and Electronic Engineering, Vol.5, Issue.2, pp.58-63, 2017.

[16] Sandeep CS, Kumar SA, Mahadevan K, Manoj P, "*Analysis of MRI and OCT Images for the Early Diagnosis of Alzheimer's Disease Using Wavelet Networks*", AMSE journal on Lectures on Modelling and Simulation, pp.31-40, 2018

[17] Sandeep C.S, Sukesh Kumar.A, K. Mahadevan, Manoj P," *Classification of OCT Images for the Early Diagnosis of Alzheimer's Disease*", IEEE International Conference on Intelligent Computing and Control (I2C2), 2017.

[18] Q. Zhang and A. Benveniste, "*Wavelet networks*," IEEE Trans. Neural Netw., Vol.3, Issue.6, pp. 889–898, 1992.

© 2018, IJCSE All Rights Reserved

[19] R. M. Balabin,R. Z. Safieva, and E. I. Lomakina,"*Wavelet neural network (WNN) approach for calibration model building based on gasoline near infrared (NIR) spectra*," J. Chemometr. Intell. Lab. Syst., Vol.93, Issue.1, pp.58–62, 2008.

[20] Sandeep C.S, Sukesh Kumar.A, K. Mahadevan, Manoj P," *Early Prognosis of Alzheimer's Disease Using Images from Fundus Camera*", IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE), 2017.

[21] Y. C. Pati and P. S. Krishnaprasad, "*Analysis and synthesis of feedforward neural networks using discrete affine wavelet tranformations*," IEEE Trans. Neur. Netw., Vol.4, Issue.1, pp.73–85, 1992.

[22] H. H. Szu, B. A. Telfer, and S. L. Kadambe, "*Neural network adaptive wavelets for signal representation and classification,"* Opt. Eng., Vol.31, Issue.9, pp.1907–1916, 1992.

[23] *H. Zhang, B. Zhang, W. Huang, and Q. Tian, "Gabor wavelet associative memory for face recognition,"* IEEE Trans. Neural Netw., Vol.16, Issue.1, pp. 275–278, 2005.

[24] O. Jemai, M. Zaied, C. B. Amar, and M. A. Alimi, "*Pyramidal hybrid approach: Wavelet network with OLS algorithm-based image classification*," Int. J. Wavel. Multir. Inf. Process., Vol.9, Issue.1, pp.111–130, 2011.

[25] R. Galvao, V. M. Becerra, and M. F. Calado, "*Linear–wavelet networks*," Int. J. Appl. Math. Comput. Sci., Vol.14, Issue.2, pp. 221–232, 2004.

[26] S. A. Billings and H. L. Wei, *"A new class of wavelet networks for nonlinear system identification*," IEEE Trans. Neural Netw., Vol.16, Issue.4, pp. 862–874, 2005.

[27] Y. Oussar and G. Dreyfus, "*Initialization by selection for wavelet network training*," Neurocomputing, Vol.34, Issue.1, pp.131–143, 2000.

[28] R. Baron and B. Girau, "*Parameterized normalization: Application to wavelet networks*," in Proc. IEEE Int. Conf. Neural Netw., Vol.2, pp.1433–1437, 1998.

[29] Michael Freeman, "*The Digital SLR Handbook. Ilex."* ,2005.

[30] Korn, Theresa M.; Korn, Granino Arthur, "*Mathematical Handbook for Scientists and Engineers: Definitions, Theorems, and Formulas for Reference and Review"*, Dover Publications. pp. 157–160, 2000.

[31] Herbert Bay, Andreas Ess, Tinne Tuytelaars, Luc Van Gool "*SURF: Speeded Up Robust Features*", Computer Vision and Image Understanding (CVIU), Vol. 110, Issue.3, pp.346–359, 2008.

[32] Jones, J.P.; Palmer, L.A., *"An evaluation of the two-dimensional gabor filter model of simple receptive fields in cat striate cortex"*, J. Neurophysiol. Vol.58, Issue.6, pp.1233–1258, 1987.

Authors Profile

Mr Sandeep.C.S, Indian received the Diploma in Electronics and Communication in 2001 from Department of Technical Education, Kerala, India, Bachelor of Engineering in Electronics and Communication in 2005 from Anna University, Chennai, India, Master of Engineering in Applied Electronics in 2007 from Anna University, Chennai, India and Master of Business Administration in Human Resource Management in 2011 from IGNOU, NewDelhi, India. Currently, he is pursuing PhD in the Department of Electronics and Communication, College of Engineering, Trivandrum, University of Kerala, India.

Prof (Dr) Sukesh Kumar.A, took B.Sc.[Engg.] in Electronics and Tele Communication Engg. in 1976 from College of Engineering,Trivandrum. ME (Tel.E) from Jadavpur University,Culcutta in 1988 and PhD from PSG College of Technology,Coimbatore,in 1999.He worked as Head of Section ,Electronics in Govt.Polytechnic ,Palakkad, and then as Lecturer,Asst. Prof.,Dean UG Studies,Dean PG Studies and retired as Principal from Govt.Engineering College,Palakkad in 2009. He also worked as Deputy Director, IHRDE, Kerala(2 years),Joint Director and Director of LBS Center for Science and technology(6 years),Executive Director in Centre for Continuing Education, Kerala(2 years), Executive Director, Centre for Foreign Student Affairs, Kerala(2years),Managing Director, Center for Advanced Printing Technology, Kerala(1½ years),and State Nodal Officer, NAAC cell, Kerala(2years).All the above are Autonomous Institutions under Govt. of Kerala. He Published 215 Papers in biomedical engineering area in various National/International Conferences/Journals. He guided 10 PhD students and currently 7 are doing PhD under him in University of Kerala. He was associated with TEQIP –Phase -I and Phase –II projects in various capacities and currently mentoring 3 Govt. Engineering colleges in Kerala and 1 Govt. Engineering college in Tamilnadu. He is also a Task force member of RUSA project in Kerala.

© 2018, IJCSE All Rights Reserved