Finally, in Chapter 6, Performance Evaluation, Conclusions and Future scope of the research work are presented.

1.5 Description of Research work

Tumor Detection Techniques using Lifting based Discrete Wavelet Transform (LDWT) and Grey Level Co-occurrence Matrix (GLCM) features with Neuro-Fuzzy Classifier (NFC) consist of four important modules.

1. The proposed 3D DWT architecture facilitates higher Compression Ratio, improves Speed and Device Utilization Factor of an automatic tumor detection system.


4. Both spatial and wavelet based features are applied to a well trained NFC and the performance of the system is evaluated using evaluation metrics namely Sensitivity, Specificity and Accuracy. The performance of the NFC system is compared with the Feed Forward Neural Network (FFNN) and Radial Basis Function (RBF) Neural Network.
CHAPTER-2

REVIEW OF LITERATURE

2.1 Introduction

Image and Video processing have become more popular and gaining wide spread usage in applications like Telemedicine, Internet Communication, Radar Signal Processing etc., The major problems associated with image processing are storage, bandwidth, bit transfer rate and hardware utilization. To overcome these problems many image processing techniques have been evolved and utilized to meet the specifications and constraints of the users. One of the most important and popular techniques adapted to overcome all the above mentioned limitations is the Lifting based Discrete Wavelet Transform (LDWT) which is superior to Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT) and Discrete Cosine Transform (DCT).

The proposed research work mainly focuses on three sections namely, 1. Lifting based 3D DWT for image and volume compression, 2. Feature extraction using Lifting DWT and Grey Level Co-occurrence Matrix (GLCM) for second order statistical texture features of medical images like CT, MRI etc., and 3. Tumor Detection and Classification in MR Images in order to find out an accurate tumor detection system. Therefore an in-depth literature review related to the above mentioned sections is presented below.

2.2 Image compression using Lifting based DWT

The data size of an image is greatly reduced by the use of an effective image compression method with allowable errors. The image compression algorithms are either Lossy or Lossless Compression Techniques. Lossy Image Compression results in less transmission time and less storage space with appreciable loss of information content where as Lossless Compression techniques give rise to the complete reconstruction of original image with minimal loss of information content in an image. As the intended
research work is concentrating on medical image analysis, it is therefore necessary to adapt lossless compression technique. The summary of literature review on image compression using DWT is presented below.

In 2001, K. C. B. Tan et al [6] proposed a novel algorithm for reducing power and area consumption of the Discrete Wavelet Transform (DWT) on CMOS-based DSP architectures. This technique reduces power by combining the data extension into the main Lifting based DWT, such that the computation steps are reduced and hence resulting in a reduction in the switched capacitance sector of the dynamic power.

In 2004, Hongyu Liao et al [7] proposed four compact and efficient hardware architectures for implementing Lifting based DWTs which are of two types, namely One dimensional (1D) and Two dimensional (2D) versions of what are called as Recursive and Dual Scan architectures.

The 2D recursive architecture is roughly 25% faster than conventional implementations and it requires a buffer that stores only a few rows of the data array instead of a fixed fraction (typically 25% or more) of the entire array. The two dimensional dual scan architecture processes the column and row transforms simultaneously and the memory buffer size is comparable with existing architectures. This architecture was used to implement Lifting scheme for wavelets.

In 2004, Pei-Yin Chen et al [8] proposed an efficient VLSI architecture for the implementation of 1D Lifting Discrete Wavelet Transform. The architecture folds the computations of all resolution levels into the same low pass and high pass units to achieve higher hardware utilization. The design is scalable for different resolution levels, because of its modular, regular and flexible structure. Since the architecture has a similar topology to a scan chain, it can be modified easily to become a testable scan based design by adding very few hardware resources. However, the proposed architecture is designed to
implement multilevel Lifting based 1D DWT concurrently and hence it is not easy to extend directly to 2D DWT design.

In 2005 X. Lan et al [9] proposed a low-power, high-speed architecture which performs two dimension forward and Inverse Discrete Wavelet Transform (IDWT) for the set of filters in JPEG 2000 by using a line-based Lifting scheme. It consists of one row processor and one column processor, each of which contains four sub filters and the row processor which is time multiplexed, perform in parallel with the column processor. Optimized shift and add operations are substituted for multiplications; edge extension is implemented by embedded circuit. The whole architecture which is optimized in the pipeline design way to speed up and achieve higher hardware utilization has been demonstrated in FPGA. Two pixels per clock cycle can be encoded at 100 MHz. The architecture can be used as a compact and independent IP core for JPEG 2000 VLSI implementation and various real time image/video applications.

In 2005, Chao-Tsung Huang et al [10], proposed three generic Random Access Memory (RAM) based architectures to efficiently construct the corresponding two dimensional architectures by using the line based method for any given hardware architecture of One Dimensional (1D) wavelet filters, including conventional convolution based and lifting based architectures. Both conventional convolution based and advanced lifting based 1D DWT modules can be flexibly integrated into the proposed architectures to obtain the optimal hardware design. The outstanding performance of the proposed architectures is demonstrated by the comparison results of the general case as well as adapting JPEG 2000 default (9, 7) and (5, 3) filters. However, the proposed architectures will be more significant only for minimal data buffer size.

In 2009, Tilo Strutz et al [11] proposed a new design method for wavelet filter banks, which is explained based on a single Lifting structure suitable for (9, 7) filter pairs. It is shown that the signal boundaries can be treated with little computational efforts. The
modification of the standard design constraints leads to families of related filter pairs with varying characteristics. It shows better performance than the standard (9, 7) filter bank for lossless image compression and competitive performance when applied in lossy compression.

In 2011, Antonius Darma Setiawan et al [12] proposed a low bit rate medical image compression scheme based on Compressive Sampling and an over complete bases set to represent the medical images as sparse as possible. This compression scheme is built based on the Compressive Samples (CS) method. It ensures high quality signal reconstruction from highly incomplete measurements (as a replacement for sampling) with overwhelming probability. The performance of the method, K-Single Value Decomposition (SVD) algorithm was better than that of the predefined DCT dictionary. This approach is suitable when a particular type a medical image is used. The result might be different, if applied to natural image.

In 2012, Mubashir Ahmad et al [13] proposed Classification of Tumors in Human Brain MRI using wavelet and Support Vector Machine. Many techniques have been developed for feature extraction from MRI, but Wavelet Transform is the best method for feature extraction. Wavelet is a non-statistical method, which gives local frequency information and detail coefficients of the image at various levels.

2.3 Feature Extraction Using Lifting based DWT (LDWT) and Grey Level Co-occurrence Matrix (GLCM)

In 2004, M. A. Tahir et al [14] proposed a method, which accelerates the computation of GLCM and Haralick texture features on reconfigurable hardware, where GLCM is one of the best known tools for texture analysis and estimates image properties related to second order statistics. These image properties, commonly known as Haralick texture features, can be used for image classification, image segmentation, remote sensing
applications etc., However, their computations are highly intensive, especially for medical images.

In 2008, Fritz Albregtsen et al [15] proposed Statistical Texture Measures Computed from Grey Level Co-occurrence Matrices to present the theory and techniques behind the Grey Level Co-occurrence Matrix (GLCM) method and the state-of-the-art of the field, as applied to two dimensional images. It does not present a solution for multi dimension images.

In 2011, Mari Partio et al [16] proposed Rock Texture Retrieval Using Grey Level Co-occurrence Matrix (GLCM), which has gained popularity in control of visual quality. This paper presents an application of GLCM to texture based similarity evaluation of rock images. This study reveals that the Co-occurrence matrix performs better for the given rock image data set. This application could reduce the cost of geological investigations by allowing improved accuracy in automatic rock sample selection. It is known that Co-occurrence Matrix approach is an effective method in classifying homogeneous stochastic textures and also in similarity evaluation of rock textures.

In 2011, Dipti Patra et al [17] proposed a method called Featured based Segmentation of colour textured images using GLCM and Markov Random Field (MRF) Model. The proposed method for image segmentation consists of two stages. In the first stage, textural features using GLCM are computed for Regions Of Interest (ROI) considered for each class. Then the statistical properties of colour textured images in Ohta colour space are explored by means of GLCM and the segmentation is done by contextual modelling of the data through MRF modelling.

In 2011, Alaa Eleyan et al [18] proposed co-occurrence matrix and its statistical features as a new approach for face recognition, which represents a technique for the distributions of the intensities and the information about relative positions of neighbouring pixels of an image. They proposed two methods to extract feature vectors using GLCM for
face classification. The first method extracts the well known Haralick features from the GLCM and the second method directly uses GLCM by converting the matrix into a vector that can be used in the classification process, which is superior to the first method. The proposed GLCM based face recognition system outperforms well known techniques, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). But its performance is not superior to local binary patterns and Gabor Wavelets. It is obvious from the results that the GLCM is a robust method for face recognition with competitive performance.

In 2012, Nitish Zulpe et al [19] proposed GLCM textural features for brain tumor classification, through which automatic recognition system for medical images became challenging task in the field of medical image processing. Medical images acquired from different modalities, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) etc., are used for the diagnosis purpose. In the medical field, brain tumor classification is very important phase for the further treatment. Human interpretation of large number of MRI slices (Normal or Abnormal) may lead to misclassification hence there is a need of such a automated recognition system, which can classify the type of the brain tumor.

In 2012, Bino Sebastian et al [20] proposed GLCM generalisation with new feature called Trace, extracted from the GLCM and its implications in texture analysis in the context of Content Based Image Retrieval (CBIR). The theoretical extension of GLCM to ‘n’ dimensional grey scale images is also discussed. The results indicate that trace features outperform Haralick features when applied to CBIR.

2.4 Tumor Detection using Lifting DWT and GLCM with Neuro-Fuzzy Classifier

In 1998, E-Liang Chen, Pau Choo Chung et al [21] proposed an automatic diagnostic system for CT Liver image classification. The system comprises a Detect Before Extract (DBE) system which automatically finds the liver boundary; a
neural network liver classifier uses specially designed feature descriptors to distinguish normal liver and two types of liver tumors, Hepatoma and Hemageoma. It is implemented by a Modified Probabilistic Neural Network (MPNN) in conjunction with feature descriptors which are generated by fractal feature information and the Grey Level Co-occurrence Matrix (GLCM). The proposed system was evaluated for 30 liver cases.

In 1999, Koen Van Leemput et al [22] proposed a fully automated method for model based tissue classification of Magnetic Resonance (MR) Images of the brain. The method interleaves classification with estimation of the model parameters, improving the classification at each iteration. This makes the method fully automated and therefore it provides objective and reproducible segmentations. There was limitation in accurate classification. Construction of more accurate brain atlas was required.

In 2001, Yongyue Zhang et al [23] proposed a novel Hidden Markov Random Field (HMRF) model for segmentation of brain images. The advantage of the HMRF model derives from the way in which the spatial information is encoded through the mutual influences of neighbouring sites. The MRF modelling has been employed in MR Image segmentation by other researchers and their findings are limited for using MRF as a general prior in a Finite Mixture (FM) model based approach. The HMRF-EM (Expectation-Maximization) framework itself is theoretically sound and the initial estimation based on thresholding is heuristic. Due to the high variability of brain MR Images in terms of their intensity ranges and contrasts between brain tissues, it is not guaranteed that the thresholding procedure will produce perfect results.

In 2003, Zhu c. et al [24] proposed a method called Multi Context Fuzzy Clustering (MCFC) on the basis of the local image model for classifying 2D and 3D MR data into tissues of white matter, grey matter and cerebral spinal fluid automatically. In MCFC, multiple clustering contexts are generated for each pixel and fuzzy clustering is independently performed in each context to calculate the degree of membership of a pixel
to each tissue class. Experimental results on both real MR Images and simulated volumetric MR data show that MCFC outperforms the classic Fuzzy C-Means (FCM) as well as other segmentation methods that deal with intensity inhomogeneities.

In 2005, Shan Shen and William Sandham[25] proposed a robust segmentation technique based on an extension to the traditional Fuzzy C-Means (FCM) clustering algorithm. A neighbourhood attraction, which is dependent on the relative location and features of neighbouring pixels, is shown to improve the segmentation performance dramatically. The degree of attraction is optimized by a Neural Network model.

In 2006, Juan Ramón Jiménez Alaniz et al [26] proposed brain MRI segmentation by applying non-parametric density estimation, using Mean Shift algorithm in the joint spatial range domain. The method was applied to synthetic and real images, keeping all parameters constant throughout the process for each type of data. The combination of region segmentation and edge detection proved to be a robust technique, as adequate clusters were automatically identified, regardless of the noise level and bias. Computation time and the information provided depend only on the image data.

In 2006, Yong Yang et al [27] proposed a segmentation method based on an extension to the conventional Fuzzy C-Means (FCM) clustering algorithm. This segmentation method is a key component of an MRI based classification system for tumors. A neighbourhood attraction, which was dependent on the relative location and features of neighbouring pixels, has been shown to enhance the segmentation performance. The degree of attraction has been optimized using a Particle Swarm Optimization model. The proposed method was proved to be superior to the conventional methods.

In 2007, S. Bricq et al [28] proposed a unifying framework for unsupervised segmentation of multi-modal brain MR Images including partial volume effect, bias field correction and information given by a probabilistic atlas. Neighbourhood information was
obtained using a Hidden Markov Chain (HMC) model. Due to the limited resolution of imaging devices, voxels may be a mixture of different tissue types; this partial volume effect is included to achieve an accurate segmentation of brain tissues. This atlas has been considered as a complementary sensor and the proposed method was also extended to multimodal brain MRI without any user tunable parameter (unsupervised algorithm).

In 2009, Arna ldo et al [29] proposed an automated scheme for MRI brain segmentation. The MRI space is represented by a high dimensional feature space that includes multi-modal intensity features and spatial features. An Adaptive Mean Shift algorithm clusters the joint spatial intensity feature space, thus the proposed method is validated on 3D single and multimodal data sets, for both simulated and real MRI data. It is shown to perform well in comparison to other state-of-the-art methods without the use of a preregistered statistical brain atlas.

In 2010, B. Caldairou et al [30] proposed a Non-Local Fuzzy Segmentation Method for brain MR Images to improve its robustness to classical image deterioration, namely noise and bias field artefacts, which arise in the MRI acquisition process. Experiments performed on both synthetic and real MRI data, leading to the classification of brain tissues into grey matter, white matter and cerebrospinal fluid. This method could be useful in the case of lower contrast imaging limited by the imaging time or challenged by inherently low contrast tissue boundaries.

In 2010, Zafer Iscan et al [31] developed a method for the detection of tumor in brain MR Images. According to the segmentation process, the head alone was extracted from the background by simply discarding the background pixels. Symmetry axis of the head in the MR Image was determined by using moment properties. Asymmetry was analyzed by using the Zernike moments of each of six tissues segmented in the head: two vectors were individually formed for the left and right hand sides of the symmetry axis on the sagittal plane by using the Zernike moments of the segmented tissues in the head.
In 2010 Qurat-ul Ain et al [32] presented a multi-phase system for tumor region extraction from the malignant brain MRI. Proposed system accurately classified the normal and tumor brain images and this was proved by the results presented. Tumor cells were also quite accurately identified by the proposed system.

In 2010, Wu Wei et al [33] proposed remote sensing image classification based on Neuro-Fuzzy and texture analysis. Classification accuracy is improved by using Neuro-Fuzzy system as classifier (NFC) and the performance of the system is investigated. This investigation indicates that all target objects including water, mountain, gobi, vegetation, desert and resident area are well separated from each other based on texture characteristics and the NFC method could get better classification results with over all accuracy of 78.3% compared to commonly used method, such as maximum likelihood classification.

In 2011, Manisha Sutar and N. J. Janwehave [34] proposed a segmentation method based on an extension to the conventional Fuzzy C-Means (FCM) clustering algorithm. This segmentation method is a key component of an MRI based classification system for tumors. A neighbourhood attraction, which was dependent on the relative location and features of neighbouring pixels has been shown to enhance the segmentation performance. The degree of attraction has been optimized by using a Particle Swarm Optimization model. The proposed method was proved to be superior to the conventional methods.

In 2012, Andac Hamamci et al [35] presented a fast and robust practical tool for segmentation of solid tumors with minimal user interaction to assist clinicians and researchers in radio surgery planning and assessment of the response to the therapy. They established the connection of the Cellular Automation (CA) based segmentation to the graph theoretic methods to show that the Iterative CA framework solved the shortest path problem. In that regard, they modified the state transition function of the CA to calculate the exact shortest path solution. Furthermore, a sensitivity parameter was introduced to adapt to the heterogeneous tumor segmentation problem and an implicit level set surface
was evolved on a tumor probability map constructed from CA states to impose spatial smoothness.

2.5 Conclusions

Segmentation of images by defining anatomical structures and regions of interest has an essential role in many medical imaging applications. A variety of techniques has been proposed to solve the problems associated with feature extraction, segmentation and detection of tumor, which are significant stages in an automatic diagnosis system. Image segmentation is an indispensable part of the tumor identification, particularly during analysis of Magnetic Resonance (MR) Images. Various methods proposed in the literature have met with only limited success due to overlapping intensity distributions of healthy tissue, tumor and surrounding edema. In order to achieve better results in detection process, it is intended to utilize Lifting 3D DWT (LDWT), Grey Level Co-occurrence Matrix (GLCM) and Neuro-Fuzzy Classifier (NFC) for classifying whether the input image is normal one or tumor image. In the proposed method, the following are the major steps, which include Pre-processing, Feature extraction and Tumor classification. Firstly, the input image is given to the pre-processing step to make suitable for further image processing steps. Then, the feature extraction method will be combined using two techniques like spatial and wavelet based methods. For spatial features, GLCM will be applied to extract texture features for images. Then, Lifting DWT will be used for wavelet based feature extraction process. Finally, the NFC is used to find whether the input MR Image is tumorous or non-tumorous. The comparative analysis is carried out with the existing Radial Basis Function Neural network (RBFN) and the Feed Forward Neural Network (FFNN) and the obtained results are analyzed in terms of evaluation metrics viz.,, Sensitivity, Specificity and Accuracy. The proposed technique will be implemented using Verilog HDL, MATLAB and performance of the proposed technique will be analyzed with the above two techniques to prove the effectiveness of the algorithm.