STUDIES ON THE PERFORMANCE ANALYSIS OF ENHANCED IMAGE FUSION TECHNIQUES

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BONAFIDE CERTIFICATE

Certified that this thesis titled **“STUDIES ON THE PERFORMANCE ANALYSIS OF ENHANCED IMAGE FUSION TECHNIQUES**” submitted for the award of the degree of **DOCTOR OF PHILOSOPHY** in **ELECTRONICS AND COMMUNICATION ENGINEERING** of the Pondicherry University, Puducherry is a record of original work done by **Ms. S.BATMAVADY** who carried out the research work under my supervision. Certified further, to the best of my knowledge, the work reported herein does not form a part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion .

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ABSTRACT

Image fusion is defined as the process of combining relevant information from two or more images captured using different sensors, in order to produce a single output image with an appealing visual perception. It is considered to be one of the most powerful tools revolutionizing the field of image processing in diverse areas like medicine, astronomy, defense and so on. For e.g., fusion of an IR image and visible image finds its application in military field. Fusion of Computed Tomography (CT) and Magnetic Resonance (MR) images provides better information in medical diagnosis.

It is really a challenging task to carry out the fusion of two images in an intelligible manner to form a composite image. The key issue is that, the salient information present in the two input images is to be preserved in the composite image formed. Many approaches to image fusion have been attempted in literature, to achieve this goal. There are mainly two groups of fusion methods: spatial domain approach and transform domain approach. Spatial domain techniques suffer from the serious drawback of spatial distortion. This drawback is overcome by using transform domain methods, of which the wavelet based techniques are found to be quite popular.

The core of the thesis work is focused on image fusion using Dual Tree Complex Wavelet Packet Transform (DTCWPT). Pixel based image fusion of two images using DTCWPT is carried out to get the final fused output and compared with that of DTCWT approach. To overcome the shortcomings encountered in pixel based fusion, region based fusion using DTCWPT is also attempted. The results obtained are compared with that of the pixel based

technique. Further work is concentrated on region based and pixel based colour image fusion using DTCWPT.

The next phase of work is concentrated on watermarking the fused image in telemedicine applications for ensuring security measures in information transfer. One such measure is embedding the details of patients in the DTCWPT coefficients of the fused medical image in the form of a watermark. Fusion of CT and MR images is considered and the fused medical image is embedded with patient information for authenticity. The noise introduced during digital transfer is also eliminated and at the receiving end, both watermark and the image are extracted successfully.

Segmentation of fused image is another challenging task in image processing and is a very important pre-processing step in the area of image analysis, computer vision and pattern recognition. In many applications, the quality of final object classification and scene interpretation depends largely on the quality of the segmented output. In segmentation, an image is partitioned into different non-overlapping homogeneous regions, where the homogeneity of a region may be composed based on different criteria such as gray level, colour or texture. While segmenting a monochrome image, a common problem arises when an image has a background of varying gray levels such as gradually changing shades. This problem is inherent since intensity is the only available information. Since, human can discern only a less than two dozen gray levels, but can distinguish amongst thousands of colours, colour image segmentation is gaining popularity in recent years.

Further, segmentation of colour images has found paramount importance in recent times, mainly due to the availability of inexpensive colour cameras associated with the decreasing computational costs. To deal with the inherent fuzziness in the digital images and to take into account both the local and global information in the image, the segmentation methods based on fuzzy techniques have been dealt in literature. Fuzzy C-Means (FCM) clustering is the widely used method for the purpose of segmentation. An advanced fuzzy clustering technique namely, Atannasov Intuitionistic Fuzzy Set (A-IFS) is also found to be an effective tool in dealing with the inherent vagueness present in the images. A novel technique merging FCM and A-IFS approach is proposed for segmenting the fused colour image. This approach involves the FCM technique for calculating membership values and A-IFS technique for the calculation of non-membership values. The proposed method yields better results both qualitatively and quantitatively.

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LIST OF ABBREVIATIONS

AIFS	Atanassov's Intuitionistic Fuzzy Sets
BPN	Back Propagation Network
CT	Computed Tomography
CWD	Concealed Weapon Detection
DCT	Discrete Cosine Transform
DTCWT	Dual Tree Complex Wavelet Transform
DTCWPT	Dual Tree Complex Wavelet Packet Transform
DWT	Discrete Wavelet Transform
FB	Filter Bank
FCM	Fuzzy C-Means
FIR	Finite Impulse Response
FT	Fourier Transform
HSI	Hue Saturation Intensity
IDTCWPT	Inverse Dual Tree Complex Wavelet Packet Transform
IFS	Intuitionistic Fuzzy Sets
IR	Infra Red
MR	Magnetic Resonance
MRA	Multi Resolution Analysis
MRI	Magnetic Resonance Imaging
MS	Maximum Selection
MSE	Mean Square Error
PCA	Principle Component Analysis
PR	Perfect Reconstruction
PSNR	Peak Signal to Noise Ratio
RGB	Red Green Blue

RMSE	Root Mean Square Error
SB	Sub bands
SIDWT	Shift Invariant Discrete Wavelet Transform
SRM	Statistical Region Merging
STFT	Short Time Fourier Transform
UIQI	Universal Image Quality Index
WA	Weighted Average
WT	Wavelet Transform

LIST OF SYMBOLS

$\Psi(t)$	Complex wavelet
$\Psi h(t)$, $\Psi g(t)$	Real wavelets
σ	Standard deviation of the distance matrix
σ_x	Standard deviation of the image x
σ_y	Standard deviation of the image y
σ_x^2	Variance of the image x
σ_y^2	Variance of the image y
$\mu_I (g_{ij})$	Degree of membership of the $(i,j)^{th}$ pixel in the image I
$\mu_{x,i}$	Membership values in each cluster
$\mu_I^{\ a}$	Average pixel intensity of the image I
$\square_I (g_{ij})$	Degree of nonmembership value of the $(i,j)^{th}$ pixel in the image I
$\square_i$	Cluster centre of i^{th} cluster
$\pi_I (g_{ij})$	Hesitancy degree at $(i,j)^{th}$ location of the pixel in the image I
δ	Impulse function
$\rho_i(g)$	Roughness index at the g^{th} intensity
c	Cluster
d	Euclidean distance
$d_T(m,n)$	Sum of the distances between a pixel at location (m,n) and its neighbouring pixels
$f_i(g)$	Histogram of the image
F_0, F_1	Filter banks
$F_i(g)$	A-IFS histon of the image

f(t)	Input to the filter bank
g_0	Low pass filter for the lower filter bank
g_1	High pass filter for the lower filter bank
g_{ij}	Gray value at $(i,j)^{th}$ location
h	Filter mask of size 3 x 3
h_0	Low pass filter for the upper filter bank
h_1	High pass filter for the upper filter bank
H	Entropy
H_0, H_1, H_0^1, H_1^1	Filter banks
HΨh(t)	Hilbert transform of real wavelet Ψh(t)
I	Image
J_{FCM}	Objective function in FCM clustering technique
m	Fuzzification factor
M	Number of row pixels
n	Number of clusters
N	Number of column pixels
N_t	Total number of pixels in the image
$P_A(r)$	Region entropy of source approximation image I_A
$P_B(r)$	Region entropy of source approximation image I_B
p x q	Image size with 'p' row pixels and 'q' column pixels
$p(x_i)$	Probability of occurrence of the i^{th} gray level
Q	Quality index
r	Number of iterations
s(n,m)	Pixel value at the location (n,m) of the input image
U	Matrix of membership values
$W_A(r)$, $W_B(r)$	Weighting factors corresponding to image A and image B respectively
W(i,j)	Embedded watermark
W'(i,j)	Retrieved watermark

x	Image 1
$\overline{x}$	Mean value of image 1
y	Image 2
$\overline{y}$	Mean value of image 2
$y(n,m)$	Pixel value at the location(n,m) of the output image
Z_x	Gray value of the pixel in a cluster

CHAPTER 1

INTRODUCTION

1.1 PREAMBLE

The rapid development taking place in the field of image processing has revolutionised the entire world today. Of late, it has become inseparable in diverse areas of Physics, Medicine, Media and so on. The origin of digital images can be traced back to early 19th century in the newspaper industry. The visual quality of images, the requirement of high storage, the need for speedy processing and transmission posed great challenges to the scientific and research community. This paved the way for the development of many of the techniques of digital image processing in 1960s. But, the computing equipment available those days was not cost effective and could not meet the ever increasing demands of this field. This situation gradually changed in 1970s and till today, this field has witnessed an enormous and vigorous growth. This can be attributed to the development of computers which go hand in hand in developing the field of image processing. Several factors like declining cost of computer equipment and the emerging of new technologies promise a continued growth in the field. With the fast computers and signal processors available in the 2000s, digital image processing has percolated into all walks of life and is considered to be the most versatile technology that has ever been developed.

The basic components of a digital image processing system comprise of image acquisition, storage module, processing stage and display. Images generated using a scanner or a camera are digitised to produce digital images. A digital image is represented by a matrix of real numbers, with each entry representing the intensity value of the pixel. Processing of images can be done either in spatial domain or in transform domain. Image enhancement, image restoration, compression, watermarking, segmentation and fusion are some of the techniques involved in image processing.

Enhancement of images is done to get a clear image, with an improved contrast. Restoration is a process of recovering the original image from the degraded image. Compression techniques are used to reduce the storage requirement and bandwidth. Watermarking can be used for ensuring security during the transfer of multimedia content. Image segmentation is an analysis technique used for separating certain features from an image and plays a dominant role in region based image fusion techniques. Of late, there is a rapid growth taking place in the field of image fusion due to the availability of affordable sensors in the market. There are also many applications which are in need of image fusion and hence, there is a steadfast growth in this horizon. The need for image fusion, the merits of wavelet based fusion, the reason for watermarking the fused image and the reason for using fuzzy techniques for segmenting the fused images are explained in the following sub-sections.

1.2 NEED FOR IMAGE FUSION

Image fusion is expected to play an important role in future due to the availability of inexpensive hardware. Often, a single sensor cannot produce better interpretation of the captured scene. Therefore, diverse images of the same scene received from dissimilar image sensors are fused into a composite image [1].

The need for image fusion is emphasized due to the following advantages:

- Overall uncertainty gets reduced because of using multiple sensors which provide redundant information and hence, this results in an increased accuracy of fused image
- In case of deterioration in performance of one or more sensors, the system can depend on other sensors. Hence, robust performance is achieved
- Complementary information obtained from different sensors allows the features in a scene to be perceived that would not be possible from individual sensors
- More timely information is available as a group of sensors can collect information of a scene more quickly than a single sensor
- Multiple sensors which operate under different operating conditions can be deployed to extend the effective range of operation. For e.g., different sensors can be used for day/night operation
- Extended spatial and temporal coverage is possible due to the joint information from different sensors
- Reliability is assured due to the integration of multiple measurements
- Compact representation of information is viable. For e.g., in remote sensing, instead of storing imagery from several spectral bands, it is comparatively more efficient to store the fused information

1.2.1 Merits of wavelet based image fusion

A wavelet is considered to be a small oscillating, non-periodic wave of limited duration characterised by finite energy. Wavelet transform can be defined as a reversible transform providing time-frequency representation of the signal and serves as an efficient tool for Multi-Resolution Analysis (MRA) of an image. It is quite popularly used in image fusion applications.

Image fusion can be performed either in spatial domain or in transform domain. Spatial domain approach suffers from the serious drawback of spatial distortion being introduced in the image. In transform based fusion techniques, DCT based fusion is prone to the problem of blocking artefacts. This drawback is circumvented by using Wavelet Transform (WT) which has revolutionised the field of image fusion on a large scale. Further, it has an advantage over Fourier Transform (FT) for representing functions that have discontinuities and sharp peaks and for accurately decomposing and reconstructing finite, non-periodic and non-stationary signals. Since, most of the real time signals including images exhibit non-stationary behaviour, FT is found to be unsuitable for such an analysis. On the other hand, Short Time Fourier Transform (STFT) was found to be suitable for the analysis of non-stationary signals, but it has fixed resolution. It gives information only about what frequency bands exist at what time intervals and no information is provided about the frequency components existing at a particular time instant. These shortcomings are easily overcome by using WT which has been found to be effective in imaging analysis. Because of the salient features exhibited by WT, it has been used as an effective tool for image fusion applications. Rich source of information on the use of Discrete Wavelet Transform (DWT) and DTCWT for image fusion application is abundantly available in literature.

1.3 NEED FOR WATERMARKING THE FUSED IMAGE

Medical health care infrastructure is based on digital information management. Although, the recent advancements in information and communication technology provide new means to access, handle and transfer medical images, they also allow easy manipulation and replication [2]. Hence, there is an urgent need for security measures in telemedicine applications. The secret information embedded in the medical images and which can be extracted at the receiving end is called watermark. The fused medical images (fused CT and MR) need to be watermarked for authentication purpose in telemedicine applications.

Watermarking can be embedded in such a way that it can be made visible or invisible. Invisible watermarking has an advantage that tampering becomes a difficult task. CT image can provide a better idea about the bony structures and the MR image is effective in highlighting the soft tissues present in the skull. Fusing these two images can help the doctors in locating the relative positions of the bony structures with respect to the tissues, which can aid in better pathological diagnosis. The fused medical image is embedded with the patient's information which is made invisible by blending it with the image, thus ensuring security in telemedicine.

1.4 NEED FOR FUZZY BASED SEGMENTATION OF FUSED IMAGE

Segmentation of fused image finds its application in many of the important image processing tasks. Segregating the object of interest is quite challenging. Therefore, efficient methods are needed to achieve this goal. One such approach is based on fuzzy techniques. Since, images are characterised by inherent fuzziness in gray values, fuzzy technique is an apt choice for segmentation of images. For instance, the clear boundary of demarcation of cancerous region from the non-cancerous part is difficult to locate in a medical image containing the tumour. Under such circumstances, fuzzy technique is considered to be a powerful tool in dealing with the vagueness present in the images, compared to other approaches. Advanced fuzzy techniques have also been developed to achieve efficient segmentation.

1.5 LITERATURE SURVEY

The extensive literature related to image fusion techniques, watermarking techniques and segmentation techniques are critically reviewed and presented.

1.5.1 Image fusion techniques

Nowadays, there is an increased affordability of imaging sensors, which has made a hallmark in multisensor vision system. The modalities of different sensors operating across different bands of electromagnetic spectrum can be combined resulting in an increased information content of the scene. Through the careful selection of complementary sensor modalities, the potential for significantly enhancing the information content in a simple image may be realised, by image fusion. However, even if different modalities are not available, image fusion can be carried out by combining multiple views of the same scene from slightly different viewpoints or from cameras with different optical capabilities. The origin of image fusion can be traced back to early 1980's [3] and has started gaining momentum thereafter, with the application of wavelets making a breakthrough in this field in recent years. Further, many applications demanding the fusion of images prompted a rapid growth in this area. For e.g., fusion of thermal and visual images for better interpretation of the scene [4] stands as a milestone for progress in this field. The need to merge visual and range data in robot navigation [5] and the possible trends in 3-D image fusion [6] also prompted further research in this field.

The simplest image fusion technique started with the pixel averaging method. In this method, a linear Weighted Average (WA) of the two source images to be fused is considered. A number of pixel-level fusion schemes in which the source images are processed and fused on a pixel basis or according to a small window in the neighbourhood of that pixel can be found in literature [7]. The pixel averaging technique can be easily implemented, fast to execute and has the advantages of suppressing any noise present in the source imagery. Unfortunately, it also suppresses the salient features present in the image, resulting in a low contrast output with a washed-out appearance. This can be reduced to some extent through the selection of optimal weights. Principal Component Analysis [8] is a popular statistical approach in finding such weights which maximises the intensity variance in the fused image. In terms of performance, the Principle Component Analysis (PCA) method is effective in applications where, one sensor is prone to produce a low contrast output and may be better ignored all together. In general, this selection property is a disadvantage. In addition, this method is sensitive to dead pixels, noise and other unwanted artefacts.

The limitations encountered in these methods led to the development of multiresolution image fusion schemes using pyramids and wavelets [9]. A general framework for multiresolution image fusion schemes has been dealt in depth in [10]. These schemes are based on extracting the salient features of each source image like edge or texture at several levels of decomposition from coarse to fine, and then intelligibly combine them to produce the fused image.

Pyramidal techniques and wavelet based techniques which fall into the category of Multiresolution Analysis (MRA) generally produce sharp, high contrast images that are clearly more appealing with greater information content . One of the earliest multiresolution techniques namely, the Laplacian pyramid originally developed for image compression was proposed by Burt and Adelson. Laplacian pyramid to image fusion application was initiated in the year 1985, which fuelled the growth of active research in this area. Each level in the Laplacian pyramid represents the difference between successive levels of the Gaussian pyramid. Since, the human visual system is more sensitive to local luminance contrast than local luminance differences, this necessitated division to be performed between different levels of pyramid rather than subtraction operation. This led to the development of contrast and the ratio of low pass pyramidal fusion schemes, in the early 1990's, with a goal of enhancing the fusion performance. The main disadvantage of the pyramid method is the over-complete set of transform coefficients, in the sense that it produces more samples than the original signal. Wavelet decomposition schemes on the other hand, overcome this shortcoming. Recent advances include the development of region based techniques which use more intelligent semantic fusion rules. The motivation for region based approach is derived from the fact that it is more reasonable to consider regions instead of individual pixels in the image. In region based approach, the source images are segmented into a set of regions that constitute the image, followed by the fusion of images [11-14]. Region based approaches help in overcoming the drawbacks such as blurring effects and sensitivity to noise, which are usually encountered in their pixel based counterpart.

Wavelet based schemes which emerged in the mid 1990s reported both qualitative and quantitative improvements over the standard pyramid techniques [15-17]. Further, these schemes also overcome the drawbacks of blocking artefacts encountered in Discrete Cosine Transform (DCT) based techniques. Hence, wavelet based techniques are widely used in image processing applications. A more detailed discussion of the application of wavelet theory to image fusion is dealt by Graham [18]. It is the most common form of transform based image fusion [19, 20] in which, the choice of fusion rule is fairly large and can include any of the techniques developed for the pyramidal fusion schemes. Further, there is also a flexibility in the choice of mother wavelet which has given rise to a large variety of wavelet based fusion algorithms [21]. In common with all the transform domain fusion techniques, the transformed images are combined in the transform domain using a defined fusion rule and then inverse transformed to produce the resultant fused image in the spatial domain.

In wavelet based techniques, DWT based image fusion [22] generally produces good results and is found to be computationally efficient. Some of the fusion rules employed in DWT based image fusion are the Maximum Selection (MS) scheme, which picks up the coefficients in each subband with the largest magnitude and WA scheme [24] which considers the weighted average of the coefficients of the two images. This led to the development of a large variety of wavelet fusion algorithms and the window based verification scheme [15]. In these schemes, a binary decision map is created to choose between each pair of coefficients using a majority decision rule. Unfortunately, DWT is not shift invariant and it lacks the phase information. Only the magnitude information is available. But, the magnitude of a coefficient alone does not necessarily reflect the true transform content at that point. Hence, this affects the comparison of wavelet coefficients in the fusion rule. Further, adverse ringing artefacts could be visualised in the fused output. Hence, perfect reconstruction of the images is questionable. This issue was addressed by Rockinger in 1997 and he came out with Shift Invariant

DWT (SIDWT) [25] with reduced over- completeness which results in visibly better fused output. The price paid for this advantage is that it is computationally more expensive than DWT. This approach towards image fusion was developed further by Bull et al in 2002 with the introduction of DTCWT [26]. The motivation for using DTCWT for image fusion applications is its better shift invariance [27], reduced over-completeness and better directional selectivity compared with that of SIDWT. The availability of phase information in DTCWT for analysis is an added advantage of using this transform. The use of DTCWT for image fusion gives considerable improvements both qualitatively and quantitatively, when compared to that of DWT as found in [28]. The fusion rules developed for DWT, the real valued wavelet transform [15,16,20,29] can be applied to the magnitude of the complex wavelet transform, since its coefficients are complex valued.

Image fusion using DTCWT can either be pixel based or region based. In pixel based image fusion using DTCWT, the wavelet coefficients of the two images are combined based on the maximum selection fusion rule to produce a single set of coefficients corresponding to the fused image. Since, it is reasonable to consider only the semantic features present in the image, rather than the individual pixels, region level fusion scheme using DTCWT gained its popularity [30]. This approach has an advantage over the pixel based technique in circumventing the drawbacks of blurring effects and sensitivity to noise. In this approach, segmentation of an image [31,32] plays a vital role for fusion to be effective. A novel algorithm applying DTCWT, for carrying out multiscale segmentation followed by Statistical Region Merging (SRM) to fine-tune the segmented output, prior to fusion operation was reported in [33]. A multifocus image fusion algorithm using DTCWT was also proposed, in which the low frequency and high frequency coefficients were fused separately using different methods, because of their different characteristics [34]. This approach was found to be successful in overcoming the drawbacks encountered in conventional wavelet based fusion algorithms. A number of modified algorithms were developed to carry out image fusion using DTCWT [35-39] yielding better improvements over the other state of the art algorithms. The judgment on the quality of the fused output mainly depends on the perception of the observer. Since the quality of visual perception depends purely on the individual and can vary from person to person, the performance of the fusion algorithm can further be substantiated by performance metrics such as Peak Signal to Noise Ratio (PSNR), Root Mean Square error (RMSE), Entropy and Universal Image Quality Index (UIQI) [40] .

The concept of DTCWT, which was introduced by Kingsbury [41-44] is extended to implement DTCWPT [45] which exhibits better shift invariance, better frequency localisation and directionality properties compared to DTCWT. It has been considered only for denoising and compression applications so far. Image fusion applications using DTCWPT is a novel idea proposed and attempted in this thesis work and is found to produce better fused output, compared to that of the latest developed DTCWT approach.

The concepts of fusion of monochrome and IR images using DTCWPT can be easily extended to colour and IR image fusion. The use of colour greatly expands the amount of information contained in an image and has been extensively researched [46]. An improved Red Green Blue (RGB) colour fusion scheme with false colour mapping was proposed by Toet [47]. An advanced colour image fusion scheme for night vision applications capable of generating a three channel false colour image was developed by Waxman et al [48] which was found to be effective in fusing a low-light visible image and a thermal IR image. Further, a region based colour image fusion technique using contourlet transform was also proposed [49]. This technique is effective in preserving the best features of the two input images in the fused output. Contourlet transform and wavelet transform have got their own advantages and disadvantages. In the proposed work, wavelet based fusion using DTCWPT is considered for pixel-level and region-level colour image fusion, as can be found in chapter 4 of the thesis. Results obtained using DTCWPT in region based colour image fusion scheme were found to be better compared to that of pixel based scheme. The results are compared both qualitatively and quantitatively.

1.5.2 Watermarking techniques

Watermarking techniques are broadly classified into spatial domain watermarking and frequency domain watermarking, each having its own advantages and disadvantages. Zhou et al proposed a spatial domain watermarking method for verifying the authenticity and integrity of digital mammography images [50]. In this method, a partial image data was replaced by one bit of the digital envelope bit stream for verifying the integrity of data. Other researchers attempted for interleaving the patient information with medical images, by replacing the lower significant bits with an embedded watermark, to reduce the storage requirements [51]. Spatial domain methods are often simpler, but are prone to spatial distortion. Therefore, majority of the present day watermarking techniques make use of the frequency domain methods based on DCT, DWT and DTCWT. Such techniques require the conversion or transformation of the original image into the frequency domain and the marks are added not to the intensity components, but to the transform coefficients [52,53]. This step is followed by inverse transformation resulting in the watermarked image. Transform domain techniques offer high robustness and ease of compression, when compared to spatial domain. But, the price paid for this advantage is that the calculations are found to be rather tedious involving complex logic. Watermark embedding done in the DC components of DCT proved to be robust [54]. But, DCT based methods are prone to blocking artefacts. Hence, wavelet based watermarking techniques gained popularity. The advantages of wavelet transform over DCT are discussed in [55]. Digital watermarks that use wavelet transform have been experimented by some researchers in the recent years [23,55-60]. These techniques exploit the frequency information and spatial information of the transformed data in multiple resolutions to gain robustness.

DWT based techniques are attractive because of their simplicity and less computational burden. The implicit features of DWT subbands i.e., the luminosity information in the low pass band and the edge information in the high pass bands were widely explored for watermarking applications. Due to the inherent disadvantage of being shift variant, DWT based techniques needed some refinement. DTCWT which has got better features when compared to DWT and which serves as a powerful tool in image analysis was found to be advantageous over other peer watermarking schemes in achieving good robustness and high watermark embedding capacity [61]. Since, DTCWPT is found to outperform DTCWT, watermark embedding in the DTCWPT coefficients of the fused image is considered in chapter 5 and is found to produce promising results compared to that of DTCWT approach.

Addition of noise [62,63] during transfer of fused image in telemedicine applications is also considered and Neural filter using Back Propagation Network (BPN) [64-66] is incorporated for the successful removal of noise without degrading the image. Since filtering techniques for the removal of noise from images is a vast ocean and also due to the reason that image fusion is the core concept considered in the work, only a drop of filtering idea is incorporated in the work. Recovery of fused medical image and extraction of watermark are also done at the receiving end. The results are compared with that of the watermarking techniques using DWT and DTCWT respectively.

1.5.3 Segmentation techniques

Image segmentation [31,32,67] is an important preliminary task which plays a crucial role in the field of medicine and other computer vision applications. It is a hot research topic gaining rapid pace in recent years. It also plays a vital role in region based image fusion techniques. Some of the approaches to image segmentation are addressed in [68]. The region based approaches to segmentation are region growing, region splitting and region splitting followed by merging. Segmentation algorithms for monochrome images generally are based on one of the two basic properties of gray level values: discontinuity and similarity. In the first category, partitioning an image is based on the abrupt changes in gray level, where detection of isolated points and detection of lines and edges in images are considered. Thresholding and region based algorithms fall into the second category. Thresholding technique based on histogram analysis is found to be the simplest in segregating the object regions and the background. The drawback of this technique is that it may result in an improper segmentation, if the valley points of the histogram are not sharp. Further, this method is based only on gray levels and does not take into account the spatial correlation of the same or similar valued elements. Each category of segmentation has got its own advantages and disadvantages. The type of segmentation to be chosen is only application specific.

Segmentation of fused image finds its applications in medical field and in further image processing tasks such as pattern recognition, machine object recognition, feature extraction etc., Segmentation technique in medical field is used for segmenting the tumour part from the non-cancerous part. Fuzzy techniques are better suited for the analysis of such complex natural systems and have been realised in various application domains. All the major ideas involved in fuzzy set theory, fuzzy logic and fuzzy systems are found in [69] and are effectively utilised in imaging analysis. These ideas on fuzzy techniques [70] lend a helping hand in dealing with the inherent imprecision in gray values present in images and fuzzy statistics has proved its superiority under such circumstances [71]. FCM [72] clustering, which is the widely used method for image segmentation is also instrumental in developing most of the other analytic fuzzy clustering approaches.

In monochrome image segmentation techniques, information is obtained only from gray values. Since, human beings intuitively feel that colour is an important part of the visual experience and also because of the reason that colour conveys more information, it is considered to be of paramount importance in image analysis. This led to the development of many fuzzy based colour image segmentation algorithms in recent years [73-81] which help in achieving a more meaningful and robust segmentation performance. However, colour image processing involves special challenges, since they are multidimensional.

FCM clustering techniques require a priori information about the number of segments and the mean or central values of the segments as initialisation points. Moreover, FCM segmentation technique has a problem of exhaustive computational burden. Therefore, the concept of rough set theory [82,83] was utilised for image analysis. It deals with the classification and extraction of knowledge from a huge data set and is useful in managing the uncertainty, particularly in medical domain. It mainly addresses the issue of vagueness and has been suitably adapted to the image processing applications domain, in order to extract the crucial information from the image for the purpose of segmentation and analysis.

A modified technique utilising the fusion of rough set theoretic approximation and FCM was addressed in [77]. It was found to be computationally efficient and effective in segmenting the natural images with gradual variations in colour. The notion of using Intuitionistic Fuzzy Sets (IFS) was developed later in order to find intuitive ways for interpreting and describing the inherent ambiguity and vagueness carried by the image [84]. IFS employing the concepts of rough set theory applied to image segmentation have gained popularity in recent years. These fuzzy sets are defined using two characteristic functions namely, membership and non-membership, which describe the belongingness or non-belongingness of an element to the universe of IFS respectively. Motivated by Zadeh's definition of fuzzy set theory, researchers were keen to bring out different notions of higher-order fuzzy sets, among which A-IFS, proposed by Atanassov [85-89] was found to be better suited for modelling the hesitancy arising from imprecise information, particularly in the field of image processing.

However, the task of intuitionistic image processing is a little complicated issue, since it involves both the membership and nonmemebership components. The imprecision in gray values of pixels arising due to quantisation noise paved a way for modelling the hesitancy using a fuzzy histogram approach [71,90]. But, the histogram based method fails to take into account the strong correlation between pixels exhibited in real world images. Hence, a fuzzy homogeneity approach which takes care of spatial correlation between pixels in the same image plane was introduced [79,91,92]. But, the correlation among the pixels in other colour planes is not considered in this method. To improve the segmentation performance, Mohabey and Ray introduced the concept of histon, which was applied to colour image segmentation [77,93]. To overcome the shortcomings of this scheme, an effective segmentation technique was proposed [78]. This method makes use of the roughness measure of rough set theoretic approach which is found to be large in object region and is close to unity. In the boundary, its value is close to zero. The roughness index based thresholding, followed by region merging is used to segregate different regions in an image effectively [78].

The concept of A-IFS proposed by Atanassov when applied to image processing applications [94-96] produced promising results. This led A-IFS in gaining popularity to establish its mark in imaging applications. Better performance of colour image segmentation could be achieved by applying the A-IFS histon based multithresholding algorithm proposed by Mushrif and Ray [80]. This method overcomes the drawbacks of the earlier methods, by taking into consideration the spatial correlation among the pixels of the same colour plane and also amongst the neighbouring pixels of other colour planes. A modification of this approach yielding better segmentation performance is proposed in the thesis work and is carried out in chapter 6. In the proposed approach, FCM technique is applied for calculating the membership values and A-IFS Histon method is employed for finding non-membership values and roughness index. The proposed method differs from [80] in the approach chosen for membership function calculation. Segmentation is followed by region merging to fine tune the segmented output. The results obtained are found to be better compared with the FCM technique and the A-IFS Histon technique.

1.6 OBJECTIVE

The main objective of the dissertation work is focused on fusion of two images captured using two different sensors, so that the composite information obtained preserves the salient features present in both the images without degrading the image quality. Both, pixel based and region based approaches are considered for visible (Gray) and IR image fusion using DTCWPT. In pixel based fusion, maximum selection scheme is adopted to produce a single set of coefficients corresponding to the fused image. The largest absolute wavelet coefficient at each location from the input images is selected as the coefficient at that particular location in the fused image. The remaining coefficients are left out, which may result in the loss of vital information.

To overcome the inherent drawback in this approach, region based fusion using DTCWPT is attempted which involves segmentation and statistical region merging, prior to fusion. The quality of the segmentation algorithm is of vital importance for the fusion process to be effective. This fusion scheme has a number of advantages over pixel based methods, as more intelligent semantic fusion rules can be considered based on actual features in the image, rather than on a single pixel or arbitrary groups of pixels. These concepts are applied to visible colour image and IR image fusion using DTCWPT and the performance is studied.

Watermarking fused medical image is also considered for telemedicine applications. Finally, the fused images are segmented using a novel fuzzy based approach . The simulation results obtained are compared qualitatively and quantitatively with the latest techniques.

The objective of the thesis work is enumerated as follows:

- Qualitative and quantitative performance enhancement in **Pixel based image fusion** technique using DTCWPT

  > for monochrome and IR image fusion

- Qualitative and quantitative performance enhancement in **Region based image fusion** technique using DTCWPT

  > for monochrome and IR image fusion

- Qualitative and quantitative performance enhancement in **Pixel based image fusion** technique using DTCWPT

  > for colour and IR image fusion

- Qualitative and quantitative performance enhancement in **Region based image fusion** technique using DTCWPT

  > for colour and IR image fusion

- Embedding of invisible **watermark** , for eg: patient information in the wavelet coefficients of the fused CT and MR image for telemedicine applications

  Removal of salt and pepper noise (which is introduced during the transmission of watermarked fused image) using Neural filter

  Extraction of the logo and recovery of medical image successfully at the receiving end

- Performance improvement of segmented fused image using **A-IFS FCM** approach

- In the image fusion and segmentation techniques considered, a number of images were taken for simulation yielding better results both qualitatively and quantitatively. The metrics chosen for performance comparison include PSNR, RMSE, entropy, normalised cross correlation and universal image quality index.

1.7 ORGANISATION OF THE THESIS

Chapter 1 gives a broad outlook of image fusion concepts and the application of wavelet transform to image fusion. Further, the need for watermarking the fused image and segmentation of fused image is also highlighted. An intensive literature survey on the topic is also dealt in depth. The prime objective of the research work and organization of the thesis are also presented in this chapter.

The reason for using DTCWPT is justified theoretically in **Chapter 2**. Further, performance comparison based on simulation is carried out which also proves the superiority of DTCWPT over DTCWT in getting a better reconstructed output. Therefore, DTCWPT is adopted for fusing **Visible (monochrome) and IR images** using **pixel based approach**. The results are compared with that of the latest DTCWT approach.

Chapter 3 discusses the steps involved in region based image fusion technique. **Region based DTCWPT approach for fusion of Visible (monochrome) and IR images** is compared with that of the region based DTCWT approach. The results obtained are also compared with the results of chapter 2.

Chapter 4 deals with **pixel and region based fusion schemes of Colour and IR images using DTCWPT.** The two images to be fused should be of same type. Whereas, in this work, one image is colour and the other image is the gray representation of the IR image. Therefore, the colour image is first converted to Hue (H), Saturation(S) and Intensity(I) components. The intensity components alone are considered for wavelet transformation. Then, the fusion of transformed intensity components of colour and IR images is carried out using the pixel based approach, based on maximum selection scheme. Next, inverse DTCWPT is taken to yield the spatial domain representation of the fused image. This fused image contains the new intensity component, to which the hue and saturation components are finally added. The Hue Saturation Intensity (HSI) colour system is then converted to RGB format. This gives the final pixel based fused colour image in spatial domain.

In region based fusion of colour and IR images, segmentation is followed by fusion of intensity images. After fusion and inverse transformation, hue and saturation components are added to the intensity components. Finally, the HSI colour system is converted to RGB format, to get the region based fused colour image in spatial domain. The performance of both the schemes are analysed and compared.

Chapter 5 deals with **watermarking of fused CT and MR image** for telemedicine applications. Watermark (logo) embedding is done in the DTCWPT coefficients and extraction is done in the other end. The original image is also recovered completely. The logo is made invisible by blending it with the fused image, so that tampering becomes difficult. Effect of noise during transmission is also considered and noise removal is done using neural filter.

Chapter 6 describes the **segmentation of fused images** by clubbing the FCM technique and A-IFS technique. The results obtained are compared with the latest approach.

Chapter 7 concludes the work by highlighting the findings that facilitated to accomplish the objectives. The possible direction for future research work is also incorporated in this chapter.

CHAPTER 2

PIXEL BASED MONOCHROME AND IR IMAGE FUSION USING DTCWPT

2.1 INTRODUCTION

DTCWT [97] is found to possess better properties such as shift invariance and less oscillations compared to the conventional Discrete Wavelet Transform (DWT). Rich source of information on wavelets can be obtained from [98-100]. In DTCWT, shift invariance can be obtained by using two parallel wavelet trees but, they are sub-sampled differently, which leads to the lack of frequency localization. The disadvantages of DTCWT are overcome in DTCWPT. The analysis and synthesis filter banks (dealt in literature) for DTCWT and DTCWPT are considered for simulation. Three levels of wavelet decomposition are considered in reconstructing the output. The simulation results demonstrate that DTCWPT yields better results both qualitatively and quantitatively in reconstructing the image compared to DTCWT. Hence, DTCWPT is adopted for pixel based image fusion of monochrome and IR images, in this chapter. The simulation results of image fusion are compared both qualitatively and quantitatively with that of the DTCWT approach.

The DWT [101-103] is obtained by filtering the signal through a series of digital filters. The input sequence is initially decomposed into low pass and high pass subbands. Each subband consists of only half the number of input samples with the purpose of providing reduced redundancy. Hence, it is found to be computationally better when compared with the continuous wavelet transform. As already enumerated, DWT is shift variant and real valued. Therefore, it does not consider phase information for analysis. The drawbacks encountered in DWT are circumvented by using Dual Tree Complex Wavelet Transform (DTCWT) which was introduced by Kingsbury [44]. In addition to the wavelet Filter Bank (FB) utilized by the DWT, the DTCWT utilizes a second wavelet FB. It is designed such that its impulse responses are approximately the discrete Hilbert transforms of those of the first wavelet FB. The output of the first FB constitutes the real part of the input coefficients and the second FB output is the imaginary part of the complex transform. For a specific signal or a set of signals, the frequency decomposition provided by the DWT and DTCWT might not be optimal.

Hence, to find a more suitable decomposition, DWPT [104] has been considered. However, like the DWT, the DWPT is also shift-variant. The most straightforward way to generate a complex dual-tree form of the DWPT is to extend each of the two DWTs to construct the DTCWT into packets themselves (DTCWPT) using the same set filters [102]. However, for several subbands in this construction, significant energy leaks into the negative frequency band. Those Sub-Bands (SB) are far from being approximately analytic.

Since DTCWPT provides the following advantages over DTCWT, it has been considered for image fusion application in the thesis work.

- Good directionality
- Shift invariance
- Good frequency localization
- Better image denoising
- Quasi analyticity

2.2 DUAL TREE COMPLEX WAVELET TRANSFORM

DTCWT is an improvement over the real wavelet transform in possessing shift invariant property. Further, in higher dimensions, it is found to be directionally selective. It is an extension of the standard real transform. It consists of a binary tree structure and is complex valued. It employs two real DWTs [105]. The real and imaginary parts of it are in fact conventional real wavelet transforms. In addition to the magnitude information, phase of CWT coefficients can be leveraged to develop a new effective wavelet based algorithms.

The analysis FB used to implement the DTCWT is shown in Figure 2.1. The two real wavelet transforms use two different sets of filters, with each satisfying the Perfect Reconstruction (PR) conditions. The overall transform is found to be approximately analytic [106]. In Figure 2.1, h0 & h_1 represent the low pass and high pass filter pair for the upper FB . Let g_0 & g_1 denote the low pass and high pass filter pair for the lower FB. 'h_0' gives the approximation coefficients of the upper tree and 'g_0' gives the approximation coefficients of the lower tree. Similarly, 'h_1' and 'g_1' give rise to detail coefficients of the upper and lower tree respectively. The two real wavelets associated with each of the two real wavelet transforms are represented as $\psi h(t)$ and $\psi g(t)$ respectively. Each differs from the other by 90^0 phase shift, i.e., these form Hilbert Transform pair. The complex wavelet is given by,

$$\psi(t)= \psi h(t) + j\psi g(t) \quad \text{and} \quad \psi g(t) = H\{\psi h(t)\} \qquad (2.1)$$

where, $H\{ \psi h(t)\}$ - Hilbert Transform of $\psi h(t)$

The filters to be constructed for DTCWPT should satisfy the following desired properties:

- Approximate half-sample delay property
- PR (can be orthogonal or biorthogonal)
- Finite Impulse Response (FIR)
- Vanishing moments/good stop band
- linear-phase

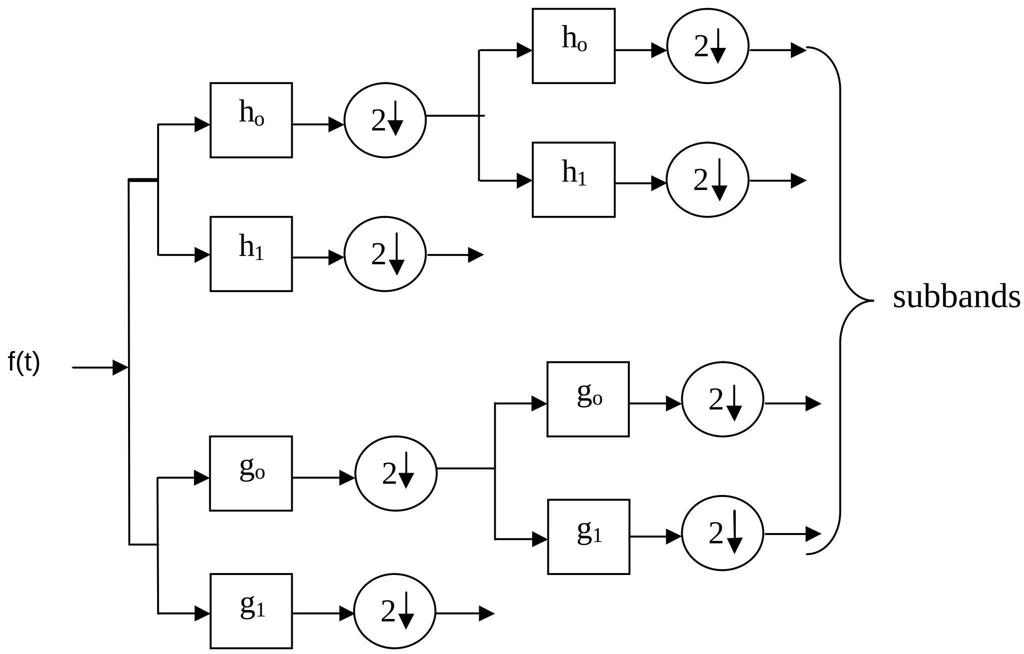

Figure 2.1 Analysis of DTCWT [44,45]

2.3 DUAL TREE COMPLEX WAVELET PACKET TRANSFORM

The wavelet packet method [45] is an extension of DTCWT which is characterised by better features. Initially, a signal is split into approximation coefficients and detail coefficients. In DTCWT, the approximation is split into a second-level approximation and detail, and the process is repeated. In DTCWPT, the detail coefficients as well as the approximation coefficients are split up till the desired levels of decomposition is achieved. The approximate coefficients represent the coarse information content of an image. The homogeneous regions in the image which are characterised by gradual changes in gray level or having more or less uniform gray values constitute the coarse information. Abrupt variations in gray values which may be found in edges form the detail- information. Low Pass Filters (LPF) are used to extract the coarse information content and High Pass Filters (HPF) are utilised to extract the detail-information.

To construct a packet form of DTCWT, each of the subbands should be repeatedly decomposed using low-pass/high pass PR FBs. The PR FBs should be chosen so that the response of each branch of the second wavelet packet FB is the discrete Hilbert transform of the corresponding branch of the first wavelet packet FB. DTCWPT consists of two wavelet packet FBs operating in parallel, where some filters in the second wavelet packet FB are the same as those in the first wavelet packet FB. The first of these two wavelet packet FBs is illustrated in Figure 2.2. The main drawback of DTCWPT is that the number of subbands is more compared to DTCWT resulting in an increased computational complexity.

In Figure 2.2, $H_0^{(1)}$ and $H_1^{(1)}$ represent the approximation and detail coefficients of the upper and lower tree respectively. $H_0^{(1)}$ and $H_1^{(1)}$ are further split into corresponding approximation coefficients H_0 and detail coefficients H_1. The approximation coefficients H_0 are further split into approximation (H_0) and detail (H_1). Similarly, detail coefficients H_1 are further split into approximation (F_0) and detail (F_1). This process is repeated for the required levels of decomposition. Three levels of decomposition is considered in the proposed work. Higher levels of decomposition would result in a better output at the cost of increased complexity.

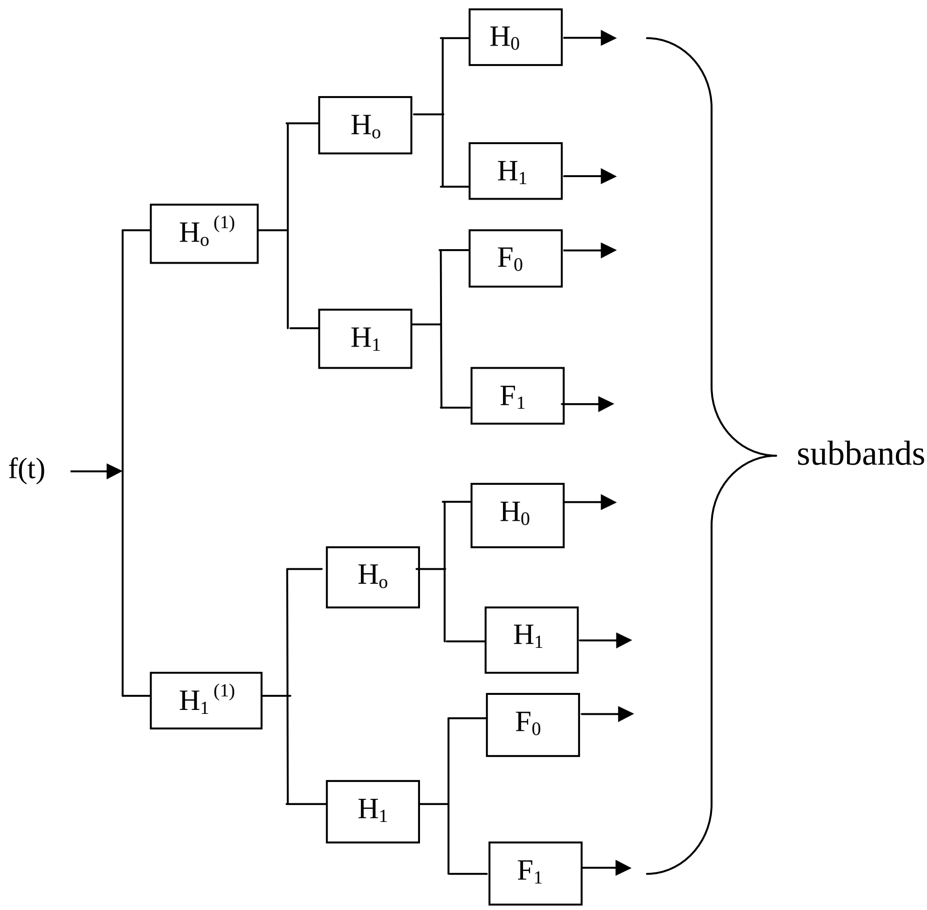

Figure 2.2 Analysis of DTCWPT [45]

2.4 PERFORMANCE COMPARISON OF DTCWT AND DTCWPT

Performance measures are deemed to be important in order to determine the beneficial aspects of wavelet transforms and also to compare the results obtained for different images. This chapter seeks to emphasize that DTCWPT provides better results when compared with DTCWT. The quantitative measures namely Mean Square Error (MSE), PSNR and entropy are considered for comparison.

MSE is a frequently used measure to find the difference between values of the input and the reconstructed output.

$$\mathrm{MSE} = \frac{1}{\mathrm{NM}} \sum_{i=1}^{N} \sum_{j=1}^{M} [s(n,m) - y(n,m)]^2 \tag{2.2}$$

where M X N corresponds to the no: of pixels in the image.

s(n,m) - Pixel value at the location (n,m) of the input image

y(n,m) – Pixel value at the location (n,m) of the output image

PSNR is the most commonly used measure to judge the quality of reconstructed image. The signal in this case is the original data and noise is the error introduced in gray values of the image during processing. PSNR is used as an approximation to human perception regarding reconstruction quality. Therefore, in some cases, one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR. A higher PSNR would normally indicate that the reconstruction is of higher quality.

$$\mathrm{PSNR} = 10 \log_{10} \left(\frac{(255)^2}{\mathrm{MSE}} \right) \tag{2.3}$$

Entropy is a measure of the average information content in an image. For an image with ‘n’ gray values, the entropy (H) is given by,

$$H = -\sum_{i-1}^{n} p(x_i)\log_b p(x_i) \tag{2.4}$$

$p(x_i)$ - probability of the occurrence of the i^{th} gray level

The qualitative comparison of DTCWT and DTCWPT are shown in Figure 2.4 and Figure 2.5 respectively. Input image, which is a Magnetic Resonance Image (MRI), is shown in Figure 2.3. DTCWPT is applied to this image and inverse transformation is done to get back the reconstructed output as depicted in Figure 2.4. Similarly, DTCWT is applied to the input image and inverse transformation is done to get the reconstructed output as shown in Figure 2.5. Analysis filter section is used for transformation and synthesis filter section is used for reconstruction of the image. The quantitative comparison of DTCWPT and DTCWT can be found in Tables 2.1 to 2.3.

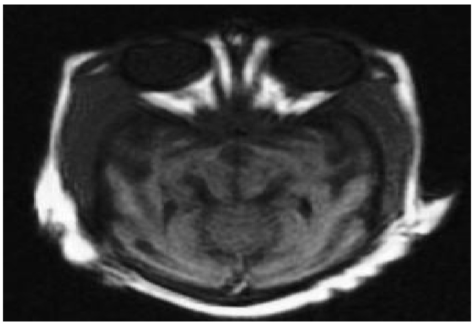

Figure 2.3 Input Image

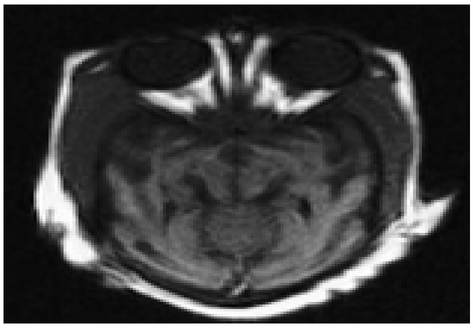

Figure 2.4 Reconstructed Output (Inverse DTCWPT)

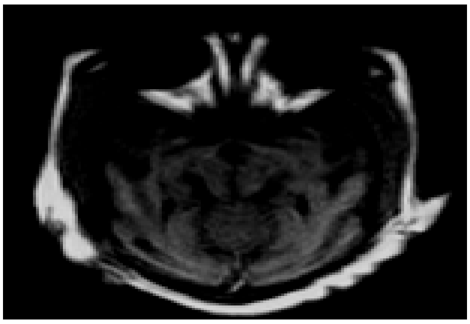

Figure 2.5 Reconstructed Output (Inverse DTCWT)

Table 2.1 Quantitative comparison in terms of MSE

IMAGES	DTCWT	DTCWPT
Barbara	41.87	32.37
Cameraman	33.88	32.81
MRI	154.55	152.78
Lena	43.9	29.11

Table 2.2 Quantitative comparison in terms of PSNR (dB)

IMAGES	DTCWT	DTCWPT
Barbara	31.91	33.03
cameraman	32.83	32.97
MRI	26.24	26.29
Lena	31.7	33.49

Table 2.3 Quantitative comparison in terms of Entropy (pixels /gray value)

IMAGES	DTCWT	DTCWPT
Barbara	6.21	7.32
cameraman	6.65	7.01
MRI	5.98	6.16
Lena	6.68	7.75

From the simulation results presented, the visual performance of DTCWPT is good when compared to DTCWT and the amount of information present in reconstructed image of DTCWPT is better than in DTCWT. Comparisons made on the basis of performance metrics also substantiate the superiority of DTCWPT over DTCWT. The above analysis provides a strong foundation for establishing the superiority of DTCWPT over DTCWT. Hence, DTCWPT is utilized for pixel based image fusion.

2.5 PIXEL BASED IMAGE FUSION

Pixel-level image fusion represents fusion of visual information of the same scene, from any number of registered image signals, obtained using different sensors. It is considered to be the simplest form of image fusion. The goal of pixel-level image fusion is to represent the visual information present in any number of input images, in a single fused image without the introduction of distortion or loss of information. Although theoretically possible, due to the redundant nature of multisensor information, the complete representation of the entire visual information from a number of input images into a single one is seldom achieved in practice. The main requirement of the fusion process then, is to identify, the most significant features in the input images and to transfer them without loss into the fused image.

The image signals produced by the sensors are input into a registration process which ensures that the input images to the fusion process correspond spatially, by geometrically warping one of them. The registered input images are fused and the resulting fused image can then be used directly for display purposes. In the work carried out, the images considered for fusion are registered images taken from literature and from database.

Fusion necessitates the following conditions to be satisfied. First, input images must be of the same scene, i.e. the fields of view of the sensors must contain a spatial overlap. Furthermore, inputs are assumed to be spatially registered and of equal size and of spatial resolution. In practice, size and resolution constraints are often satisfied by re-sampling one of the input images. Another important consideration in pixel-level fusion is the number of input images and the colour characteristics of the input and output images.

When considering colour instead of monochrome images, there are two fusion possibilities, i.e. fusion of monochrome images to produce a pseudo colour fused image, and fusion of colour and monochrome images to give a true colour fused image. But monochrome fusion can be easily extended to the latter case by applying monochrome fusion on the individual channels of the colour representations. Pseudo colour fusion however, requires an understanding of colour perception properties and is not a straightforward extension of the monochrome fusion case.

The pixel based approach is summarized as follows:

1) Two images, of which one is a visible monochrome image and the other an IR image, are considered for image fusion.

2) DTCWPT is taken for the intensity components of image 1 and image 2 respectively.

3) The maximum selection rule is applied to find the largest absolute wavelet coefficient at each location of the input images to produce a single set of coefficients in the fused image

4) Inverse DTCWPT is applied to get the final fused output in spatial domain

2.5.1 Flowchart for pixel based image fusion

The steps involved in pixel based image fusion using DTCWPT are illustrated diagrammatically in Figure 2.6.

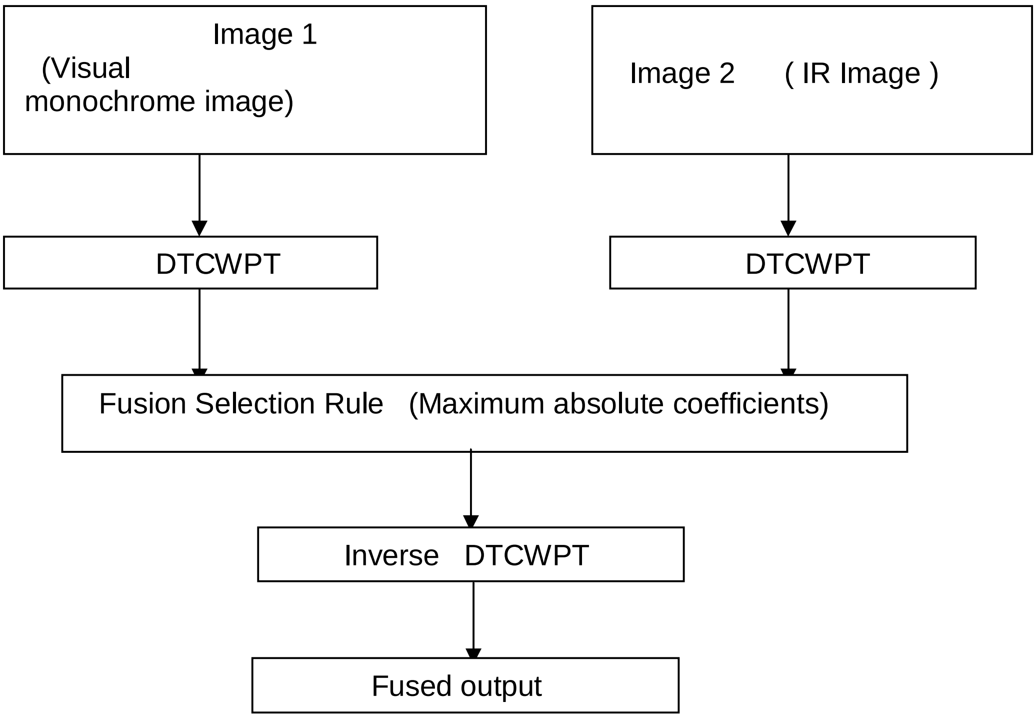

Figure 2.6 Flowchart for pixel based image fusion

2.6 RESULTS AND DISCUSSION

Since DTCWPT based image fusion is not available in the MATLAB toolbox, programs are written in MATLAB to carry out pixel based image fusion using DTCWPT and the results obtained from simulation are compared with that of DTCWT, both qualitatively and quantitatively. In all the examples shown, two images corresponding to two different sensors are considered for fusion and the fused results obtained by employing DTCWPT and DTCWT are also shown. Out of the two images chosen for fusion, one is a visible image (monochrome) and the other, an IR image.

2.6.1 Qualitative performance comparison

EXAMPLE 1

Figure 2.7 (a) IR image

Figure 2.7(b) Visual image

Figure 2.7(c) Fused Output (DTCWPT)

Figure 2.7(d) Fused Output (DTCWT)

Figure 2.7 Pixel based fused output (monochrome) using DTCWPT and DTCWT for EXAMPLE 1

In this example, Figure 2.7(a) is an input IR image of poor resolution and the bush is not clearly visible. Figure 2.7(b) is a monochrome visual image captured using visual sensors. Merging image 1 and image 2 would provide the fused output. This is a typical scenario, which may of use in military applications. Visually, the fused output in DTCWPT based technique of Figure 2.7(c) seems to be more or less coincident with that of DTCWT. But, close observation reflects a sort of checkerboard pattern slightly visible in DTCWT based output of Figure 2.7(d). Even though, overall fused output conveys the salient information in both cases of this particular example, a slight deviation in performance cannot be tolerated in medical imaging applications and may result in an erroneous diagnosis.

EXAMPLE 2

Figure 2.8(a) (IR image)

Figure 2.8(b) (Visual image)

Figure 2.8(c) Fused Output (DTCWPT)

Figure 2.8(d) Fused Output (DTCWT)

Figure 2.8 Pixel based fused output (monochrome) using DTCWPT and DTCWT for EXAMPLE 2

Generally speaking, many IR sensors use the temperature distribution of the target to produce an IR image. Due to the limitations of an IR image in capturing all the relevant visual information, the IR images alone are not sufficient enough to detect the target precisely with its location. This issue demands the need for fusing the IR image with the image captured in visual frequency range of the same scene.

In this example, fusion of IR image and Visual image is done using pixel based approach. A person could be located in Figure 2.8(a) (IR image), whereas the fence is not clearly visible in this image. In Figure 2.8(b), (Visual image), fence is clearly visible, but the person could not be located due to the limitations of visual sensors. The fused output preserves the salient information present in both the input images, locating the person and the fence. The fused output using the pixel based approach based on DTCWPT and DTCWT are also shown in Figure 2.8(c) and Figure 2.8(d) respectively.

EXAMPLE 3

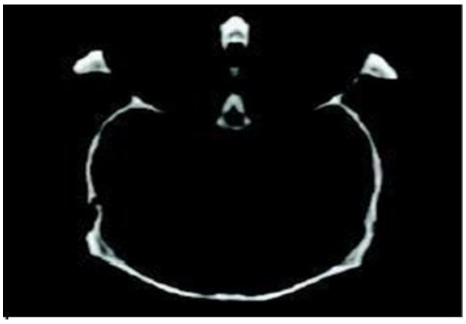

Figure 2.9(a) (CT Image)

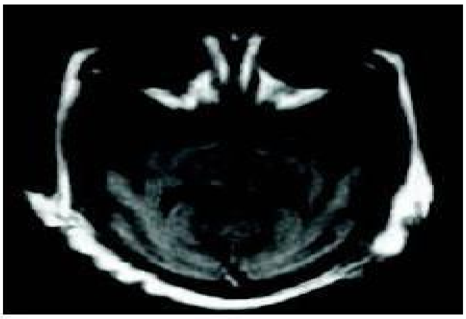

Figure 2.9(b) (MR Image)

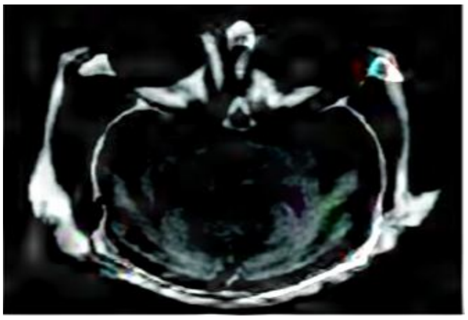

Figure 2.9(c) Fused Output (DTCWPT)

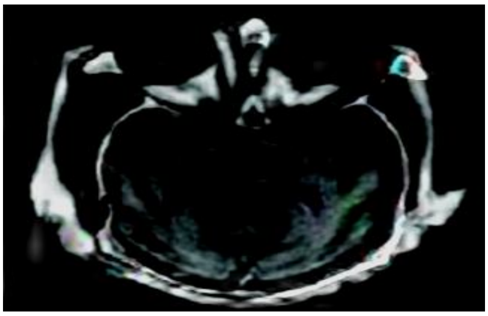

Figure 2.9(d) Fused Output (DTCWT)

Figure 2.9 Pixel based fused output (monochrome) using DTCWPT and DTCWT for EXAMPLE3

In example 3, the CT image shown in Figure 2.9(a) and MR image depicted in Figure 2.9(b) are fused. The CT image gives a clear picture of bony structures and MR image shows the soft tissues present. Merging these two images would assist the doctor in locating the relative positions of the bony structures with respect to the tissues which may be of use in pathological diagnosis. The DTCWPT based fused output and DTCWT based fused output can be seen in Figure 2.9(c) and Figure 2.9(d) respectively. Both CT and MR images together can be seen in the composite fused output.

In some of the examples considered, superior performance of DTCWPT can be visualized. But, small variations in the gray values are difficult to be distinguished. Further, visual judgment may vary from person to person depending upon his/her perception and it would be highly difficult to differentiate the gray levels compared to colour information. Since, DTCWPT allows the splitting of approximate as well as the detail coefficients, intuitively its performance should be better than that of DTCWT. The price paid for this advantage is increased computational complexity involving more number of subbands. In order to substantiate the results obtained, a comparison is made using different performance metrics which validates the superiority of using DTCWPT over DTCWT.

2.6.2 Quantitative performance comparison

Performance comparison of pixel based image fusion using DTCWT and DTCWPT using the metrics, PSNR and MSE are as shown in Figure 2.10 and Figure 2.11 respectively.

2.6.2.1 PSNR comparison

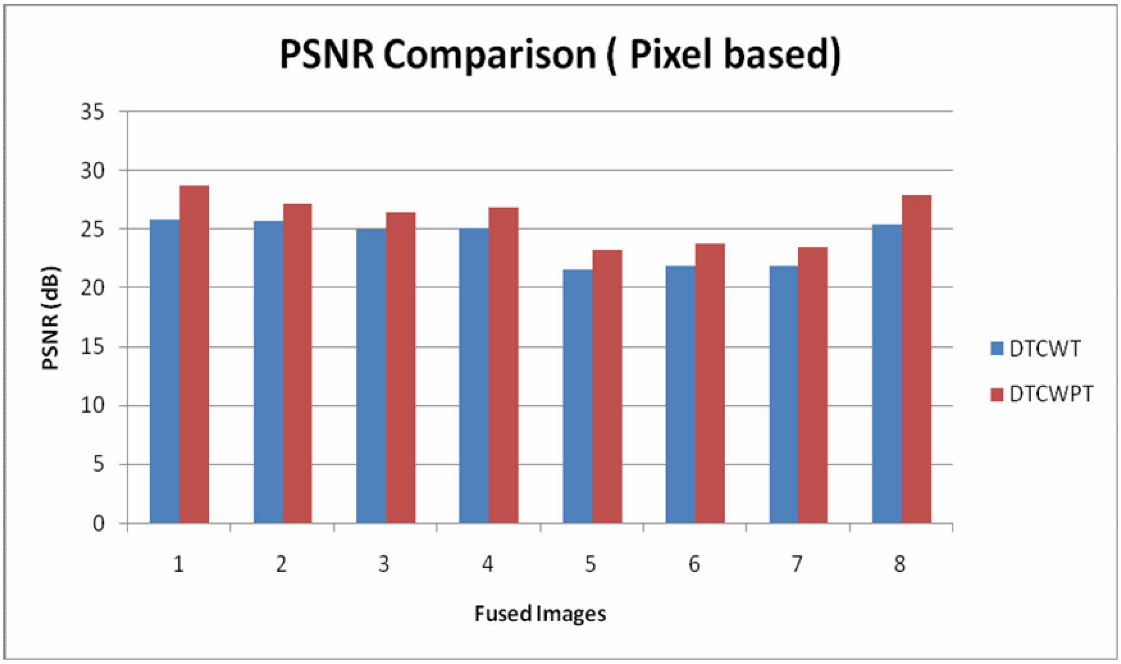

Figure 2.10 PSNR Comparison for pixel based fused images using DTCWT and DTCWPT approaches

The PSNR values in the case of pixel based image fusion using DTCWPT are found to be higher than that of DTCWT. Higher the value of PSNR, the fused output will be better. Obviously, MSE values are found to be lower in the case of DTCWPT based image fusion.

2.6.2.2 MSE comparison

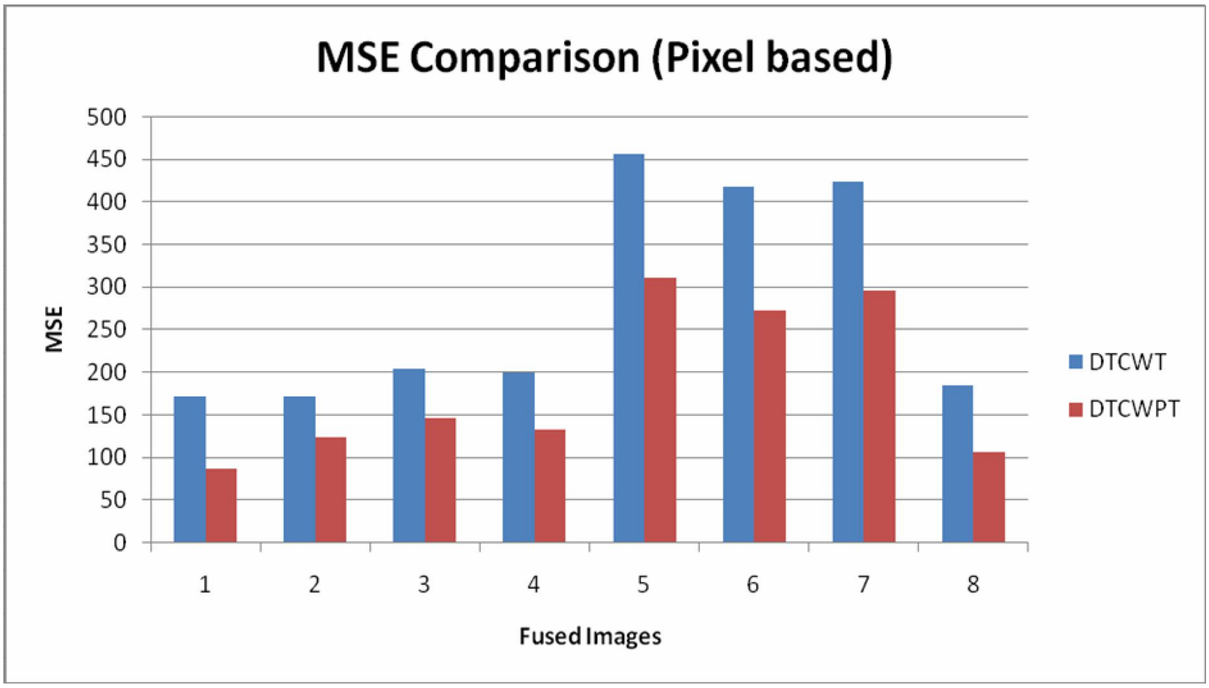

Figure 2.11 MSE Comparison for Pixel based fused images using DTCWT and DTCWPT approaches

2.7 CONCLUSION

From the simulations carried out, it is inferred that DTCWPT performs better than DTCWT in producing a better reconstructed output both qualitatively and quantitatively in terms of PSNR, MSE and entropy. Further, pixel based image fusion using DTCWPT outperforms DTCWT based fusion, due to the reasons already justified. Pixel based image fusion depends on a one-to-one comparison of the wavelet coefficients of the two images and chooses only the maximum absolute values as the coefficients corresponding to the fused output. The other coefficients are left out and are not considered in the fused image. Hence, this technique has its inherent drawbacks like blurring, sensitivity to noise etc., Sometimes, there may be a loss of vital information like reduced contrast and distortion (false information getting introduced) in the fused output which pays a heavy price , particularly in the case of medical imaging. The amount of noise distortion present in the fused image also reduces fusion performance. The larger the loss of information, the worse the performance of the fusion algorithm. To alleviate these problems, region based image fusion of visible (monochrome) image and IR image is considered in the following chapter.

CHAPTER 3

REGION BASED MONOCHROME AND IR IMAGE FUSION USING DTCWPT

3.1 INTRODUCTION

In many pixel based image fusion techniques, the coefficients of the input image are processed individually. Moreover, most of these techniques provide poor results in extracting the vital information. Fusion methods based on relatively simple image processing techniques using averaging method, generally do not take into account the subject-relevant information or the features that exist in the source images. If the feature information is not incorporated in the fusion process, it could lead to undesirable effects such as artefacts or inconsistencies and the loss of vital information in the fused image. Therefore, the wavelet based pixel fusion method should combine the aspects of a feature selection rule for implementation. The fusion process is guided by the salient directional features identified at the multi-scale detail images. This is done by comparing the intensity of the corresponding pixels or an arbitrary area around the sampled pixel defined by a fixed size window in the corresponding detail images, and selecting the one deemed more important for the fused pyramid.

The majority of applications of a fusion scheme are interested in features within the image and not the actual pixels. Hence, it is meaningful and reasonable to combine the semantic features intelligibly rather than pixels in the fusion process. This has led to the popularity of region based image fusion schemes. A number of region based image fusion schemes have been proposed in the literature [1,10-14,30,48]. Compared to pixel-level image fusion schemes, region based fusion schemes are less sensitive to noise. The region based wavelet transform technique is also vulnerable to noise to some extent as it classifies all noise to new regions with different frequency bands. The effect of noise in this case, can however be suppressed using advanced wavelet transforms like DTCWT and DTCWPT, which possess properties like shift invariance and directionality. DTCWPT provides better directionality, shift invariance and better image denoising compared to DTCWT.

So far, DTCWT has been found to be the best transform technique for image fusion, in wavelet domain. Region based image fusion scheme attempted using DTCWPT is a novel idea proposed in this chapter. Two images captured using two different sensors of the same scene are considered for region based image fusion. The proposed approach involves applying DTCWPT to the first image followed by filtering operation, binary segmentation, multiscale segmentation and statistical region merging. The same process is repeated for the second image also. This is followed by a fusion decision to be taken to merge the regions of the two images in the transform domain. Finally, Inverse Dual Tree Complex Wavelet Packet Transformation (IDTCWPT) yields the fused output in spatial domain. Segmentation and statistical region merging are the crucial steps, which need more attention as these are the deciding factors for an effective fusion strategy in a region based fusion scheme.

3.2 REGION BASED SEGMENTATION

Region based image fusion algorithms are found to be more robust , less vulnerable to noise and misregistration. These schemes are based on segmenting the two source images into regions of interest, by using an appropriate segmentation technique. This step is followed by fusion of images.

The region information of the two source images is to be utilised effectively, so that enhanced information content could be realised in the fused output.

In the segmentation step involved, an image is partitioned into a number of disjoint regions, where each region is homogeneous in terms of colour, gray level or texture. Image segmentation algorithms may be generally classified into discontinuity-based methods and similarity based methods. The boundary or interface between two homogenous regions is usually defined by a discontinuity in gray level, colour or texture. Discontinuity based methods therefore partition an image based on the detection of such discontinuity. Segmentation based on the similarity method is carried out by detecting the homogeneity between pixels and regions and the image is segmented according to certain pre-defined criteria or levels.

The classic approach to segment an image is to apply a gradient and then threshold the resulting gradient image. However, it is difficult to select an appropriate value for thresholding. If the threshold value is too low, false edges and noise are picked up and lead to inaccurate segmentation. Conversely, edges may not be detected, if the threshold is too high. As a result, broken gradients would form and result in poor segmentation. An alternative method based on morphological principles, watershed transformation, has evolved and has become a well established approach for the segmentation of images.

The quality of the image segmentation plays a predominant role in a region based fusion approach. An effective segmentation technique is the one , which is capable of locating all the salient objects present in an image. At the same time, it should be capable of partitioning the regions in an efficient manner. If a feature is split into more than one region, each will be treated separately and may introduce artefacts into the fused image. If a feature is missed, it will not be incorporated in the fused image. The segmentation algorithm should be able to locate the region boundaries precisely, in order to eliminate the blocking and blurring effects in the fused output. Since, it is reasonable to combine the regions of the two images rather than the pixels, region based image fusion techniques have gained popularity. There are a number of perceived advantages of combining a region-level fusion strategy with statistical techniques leading to the reduction in noise .

Each approach to segmentation has its own pros and cons in terms of applicability, performance, computational cost etc. However, to deal with the inherent ambiguity or vagueness present in the image, fuzzy based clustering approach is considered to be an apt choice for segmentation of images.

Guidelines for defining region based segmentation are given as follows:

1) Regions of a segmented image should be uniform and homogeneous with respect to some characteristic such as gray tone or texture.

2) Region interiors should be simple and without many small holes.

3) Adjacent regions of segmentation should have significantly different values with respect to the characteristics on which they are uniform.

4) Boundaries of each segment should be simple and must be spatially accurate.

3.3 STATISTICAL REGION MERGING

Region merging is an important process to be considered prior to fusion in order to fine-tune the segmentation output. It is a noise cleaning procedure used to discriminate against small segments and merge them to produce a smoother image. The fusion technique is applied as a post processing step after clustering. The merging method is also able to reduce the number of clusters that exists within an image, if the regions that are occupied by the cluster is small enough. Many of the regions merging methods face some shortcomings in determining seed points in an image to start the merging process and the problem of under or over segmenting. These fusion methods do not require any determination of seed values as each pixel in the image is considered as a seed value. The main use of region merging algorithm does not over or under segment the image to the extent that the image is unrecognizable. This algorithm is mainly used to remove small cluster sizes and the number of clusters that are detected in the clustering phase. Statistical parameters such as the mean intensity difference between adjacent clusters are used for merging the adjacent segments.

3.4 FUSION STRATEGY

A popular way to construct the fused approximation image ‘ I_F’ from the given images, ‘I_A’ and ‘ I_B’ is given by,

$$I_F = (I_A + I_B) / 2, \tag{3.1}$$

I_A - Image A

I_B - Image B

The region entropy is used to measure the amount of salient information from the approximation images contributing to the fused result.

Hence, the composite approximation image is generated by using the weighted combination, given by,

$$I_F(r)=W_A(r)I_A r) + W_B(r) I_B(r) \quad (3.2)$$

$$W_A(r) = \frac{P_A(r)}{P_A(r) + P_B(r)} \quad (3.3)$$

$$W_B(r)=1-W_A(r) \quad (3.4)$$

$W_A(r)$, $W_B(r)$ – Weighting factors

$P_A(r)$ - region entropy of source image I_A

$P_B(r)$ - region entropy of source image I_B

The two images are fused based on region features in transform domain. Finally, inverse transformation yields the fused output in spatial domain.

3.5 STEPS INVOLVED IN REGION BASED FUSION

The main steps involved in region based fusion scheme (monochrome and IR image) are summarized as follows:

1) DTCWPT is applied to IR image 1 and visible monochrome image 2

2) Region based segmentation is carried out using fuzzy clustering to segment the regions in image 1 and image 2.

3) Statistical region merging is done to fine-tune the segmented output

4) Fusion decision is taken based on the region features of image 1 and image 2

5) The approximate images are combined in transform domain

6) Inverse DTCWPT is taken to get the fused image in the spatial domain

3.5.1 Flowchart representation for region based image fusion

Region based image fusion using DTCWPT can be represented diagrammatically in Figure 3.1.

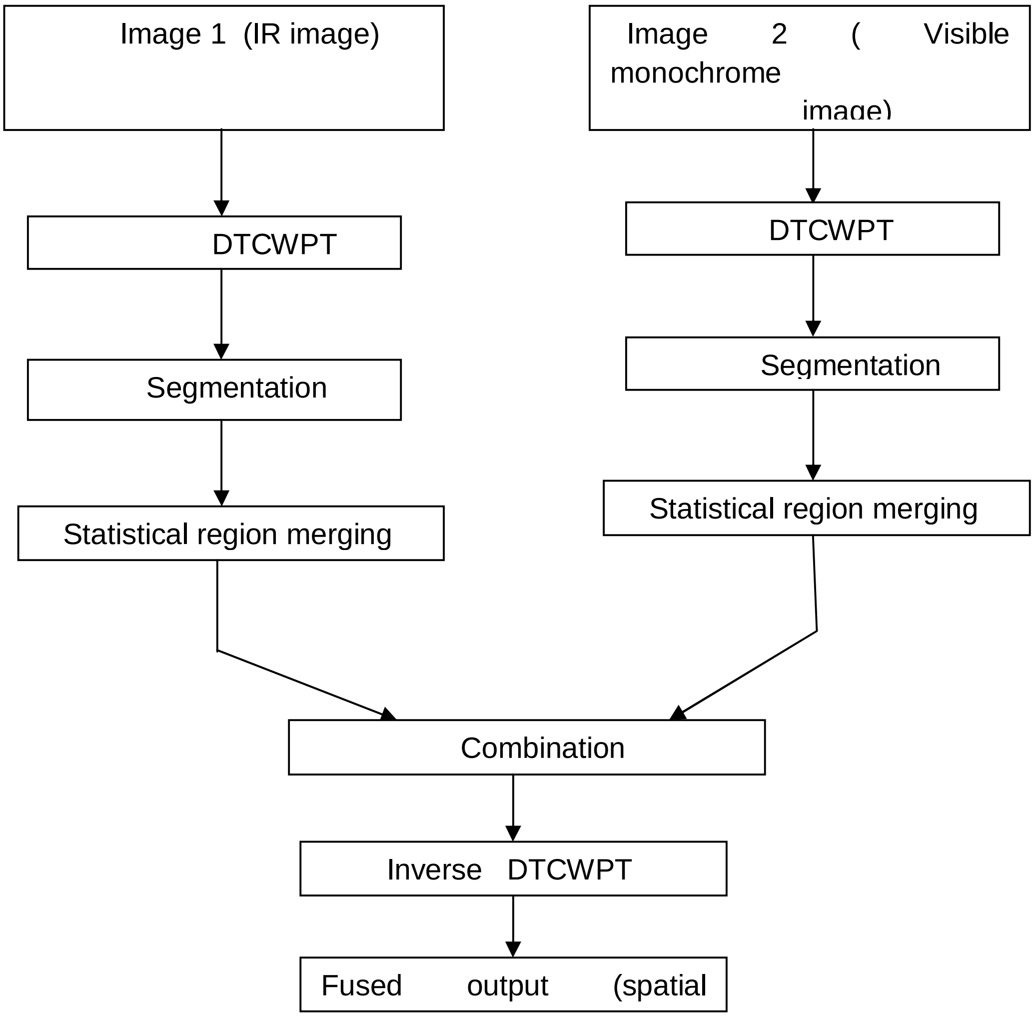

Figure 3.1 Flowchart for region based image fusion using DTCWPT

3.6 RESULTS AND DISCUSSION

3.6.1 Qualitative performance comparison

EXAMPLE 1

Figure 3.2 (a)

IR Image

Figure 3.2(b)

Filtered binary image

Figure 3.2(c)

Multiscale segmentation

Figure 3.2(d)

After Statistical region merging

Figure 3.2 Segmented output of IR image of EXAMPLE 1

In this example, an IR image shown in Figure 3.2(a) is considered which is to be fused with the visual image of Figure 3.3(a). DTCWPT is applied to this image which is then median filtered in order to have uniform characterisation of texture. It is also used to achieve excellent noise reduction capabilities with less blurring. Then, binary segmentation is carried out. Figure 3.2(b) represents the filtered and binary segmented image. This step is followed by multiscale segmentation (the use of varying window sizes by which the source images are partitioned into relatively homogeneous regions) which is depicted in Figure 3.2(c). A bigger window size is used for high scales which are useful for locating the boundaries and lower scales are used for localising the intensity values. It is reasonable to apply lower scales to nontextured regions, which contain relatively homogeneous texture, while higher scales are adopted for the textured regions to capture the texture boundaries.

To fine-tune the segmented output, statistical region merging is done. Figure 3.2(d) shows the output obtained after statistical region merging. Multiscale segmented output in Figure 3.2(c) is represented by pseudo colouring using the command label2rgb in MATLAB, in order to have better perception of different regions.

Figure 3.3(a)
Visual image

Figure 3.3(b)
Filtered binary image

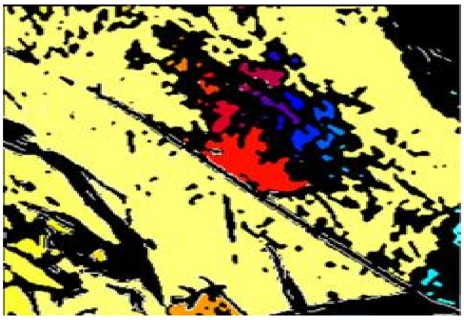

Figure 3.3(c)

Multiscale segmentation

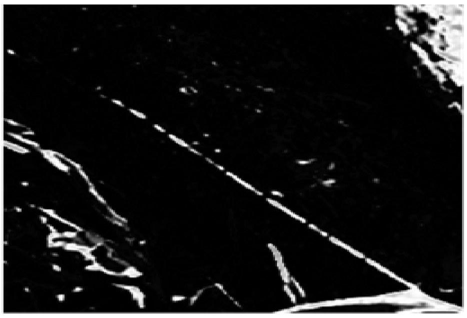

Figure 3.3(d)

After Statistical region merging

Figure 3.3 Segmented output of Visual image of EXAMPLE 1

The steps carried out for IR image is repeated for visual image. Figure 3.3(b) is the filtered binary segmented image. Multiscale segmentation output in pseudo colouring is shown in Figure 3.3(c). Statistical region merging is done to fine-tune the segmented output, which is displayed in Figure 3.3(d). Combination of both the images after statistical region merging is carried out in transform domain. This is then followed by IDTCWPT to yield the final fused output in spatial domain. Fusion is done using the same procedure by applying DTCWT also. The fused output using DTCWPT and DTCWT for region based image fusion are shown in Figure 3.4 and Figure 3.5 respectively. Careful observation shows that DTCWPT fused output is better. The result obtained is further substantiated using performance comparison based on PSNR and MSE. A few more examples are also considered for similar analysis.

Figure 3.4 Fused output of EXAMPLE1 (DTCWPT)

Figure 3.5 Fused output of EXAMPLE 1 (DTCWT)

EXAMPLE 2

Figure 3.6(a) IR Image

Figure 3.6(b) Filtered binary image

Figure 3.6(c) Multiscale segmentation

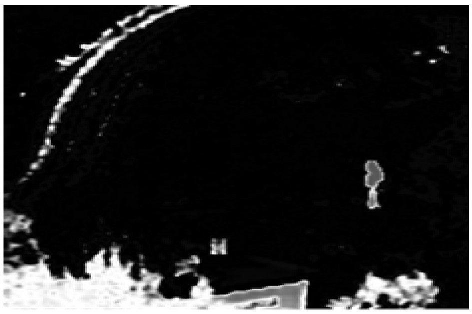

Figure 3.6(d) After Statistical region merging

Figure 3.6 Segmented output of IR image of EXAMPLE 2

In this example, IR image shown in Figure 3.6(a) is fused with the visual image of Figure 3.7(a). The filtered and binary segmented IR image is shown in Figure 3.6(b). For visual image, the filtered binary output is displayed in Figure 3.7(b). The output obtained after multiscale segmentation for IR and visual images are shown in Figure 3.6(c) and Figure 3.7(c) respectively. Figure 3.6(d) gives the output obtained after statistical region merging, for IR image. Similar output for visual image can be seen in Figure 3.7(d). The fused output based on DTCWPT and DTCWT can be found from Figure 3.8 and Figure 3.9 respectively.

Figure 3.7(a) Visual Image

Figure 3.7(b)
Filtered binary image

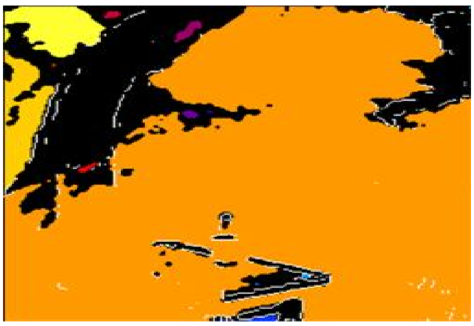

Figure 3.7(c)
Multiscale segmentation

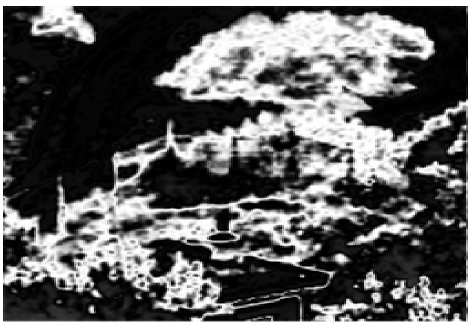

Figure 3.7(d)
After Statistical region merging

Figure 3.7 Segmented output of Visual image of EXAMPLE 2

Figure 3.8 Fused Output of EXAMPLE 2 (DTCWPT)

Figure 3.9 Fused output of EXAMPLE 2 (DTCWT)

EXAMPLE 3

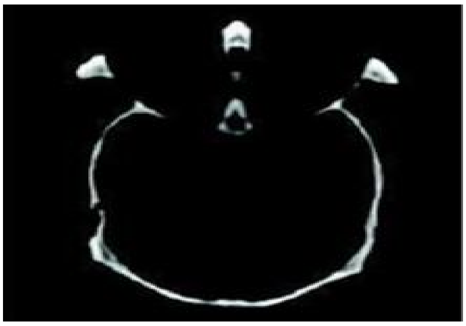

Figure 3.10(a) CT image

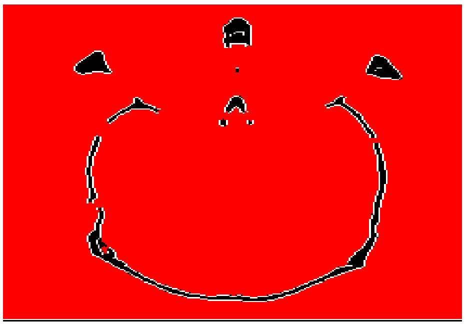

Figure 3.10(b) Multiscale segmentation

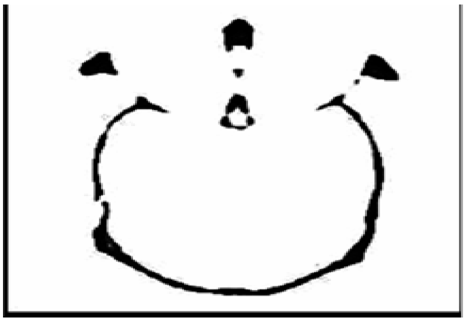

Figure 3.10(c) After Statistical region merging

Figure 3.10 Segmented output of CT image of EXAMPLE 3

In this example, the CT image shown in Figure 3.10(a) is fused with the MR image of Figure 3.11(a) to yield the fused output shown in Figure 3.12 and Figure 3.13, for DTCWPT and DTCWT based approaches respectively. The output obtained after intermediate processing steps for CT image are shown in Figure 3.10(b) and Figure 3.10(c). Figure 3.11(b) and Figure 3.11(c) give the similar output obtained for MR image.

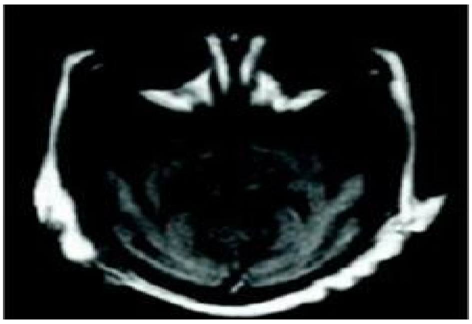

Figure 3.11(a) MR Image

Figure 3.11(b) Multiscale segmentation

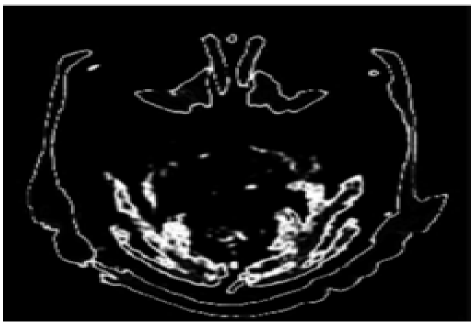

Figure 3.11(c)

After Statistical region merging

Figure 3.11 Segmented output of MR image of EXAMPLE 3

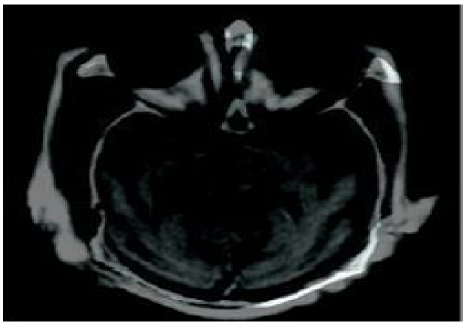

Figure 3.12 Fused Output of EXAMPLE 3 (DTCWPT)

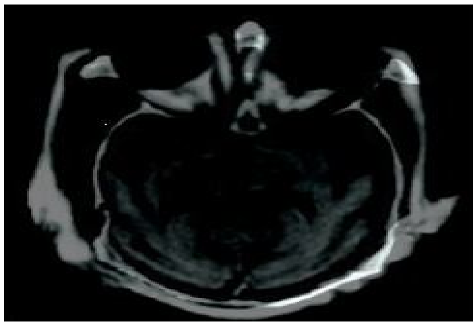

Figure 3.13 Fused Output of EXAMPLE 3 (DTCWT)

In some of the examples shown, the output of DTCWPT seems to be almost indistinguishable from the DTCWPT output. It once again depends on the perception of the observer. But, in medical imaging, even a slight variation may result in faulty diagnosis. Further, it would be highly difficult to differentiate the gray level variations, if the changes in gray levels are not distinct. However, quantitative analysis establishes the superiority of DTCWPT in region based fusion over that of DTCWT. The proposed technique differs from that of the pixel based technique in incorporating the segmentation step prior to fusion. Compared to the pixel based approach which suffers from blurring, this technique improves the contrast of the image.

3.6.2 Quantitative performance comparison

Eight fused images are considered for performance comparisons in terms of PSNR (Figure 3.14) and MSE (Figure 3.15) using DTCWT and DTCWPT in region based image fusion approach. From the results, one can infer that region based image fusion employing DTCWPT outperforms the DTCWT approach in yielding high PSNR values and low MSE values.

3.6.2.1 PSNR comparison

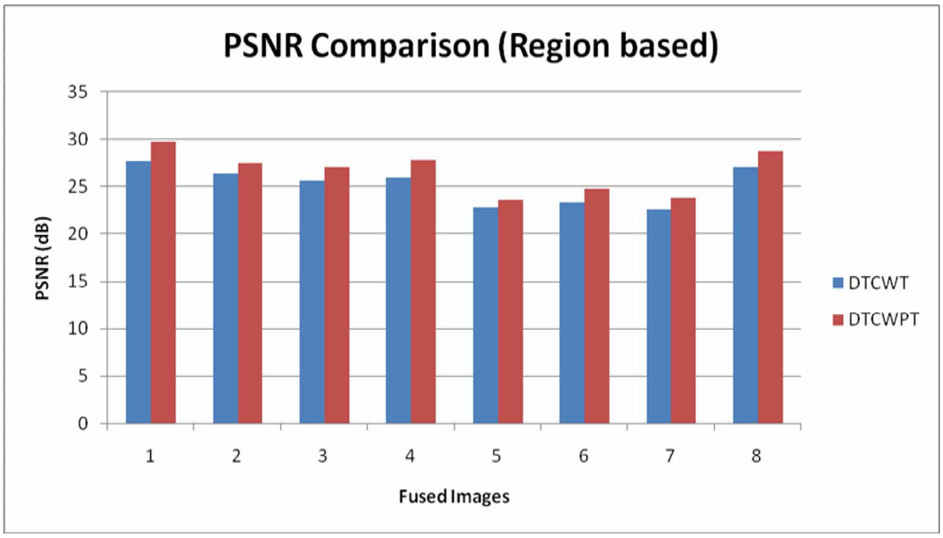

Figure 3.14 PSNR comparison for region based fused images using DTCWT and DTCWPT based approaches

3.6.2.2 MSE comparison

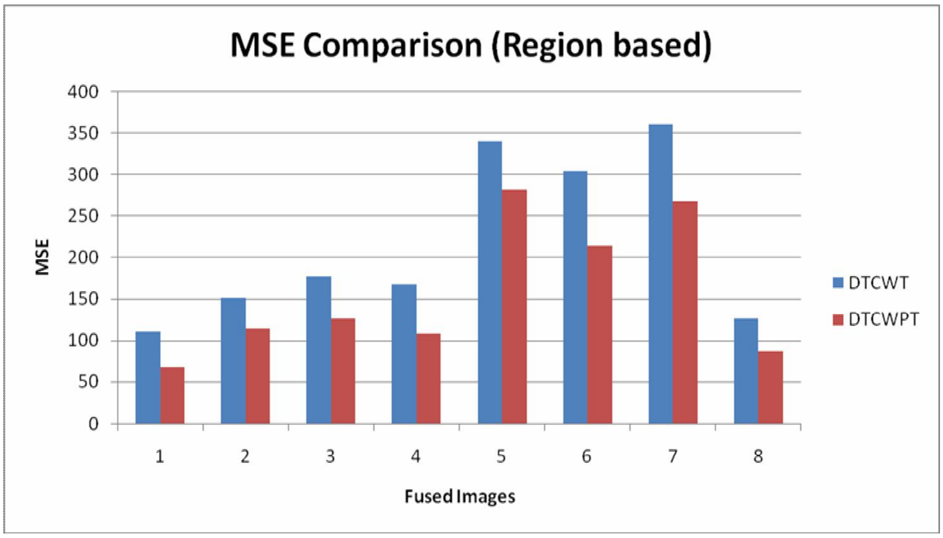

Figure 3.15 MSE comparison for fused images using DTCWT and DTCWPT approaches

3.6.3 Overall performance comparison of pixel based and region based image fusion

3.6.3.1 PSNR comparison

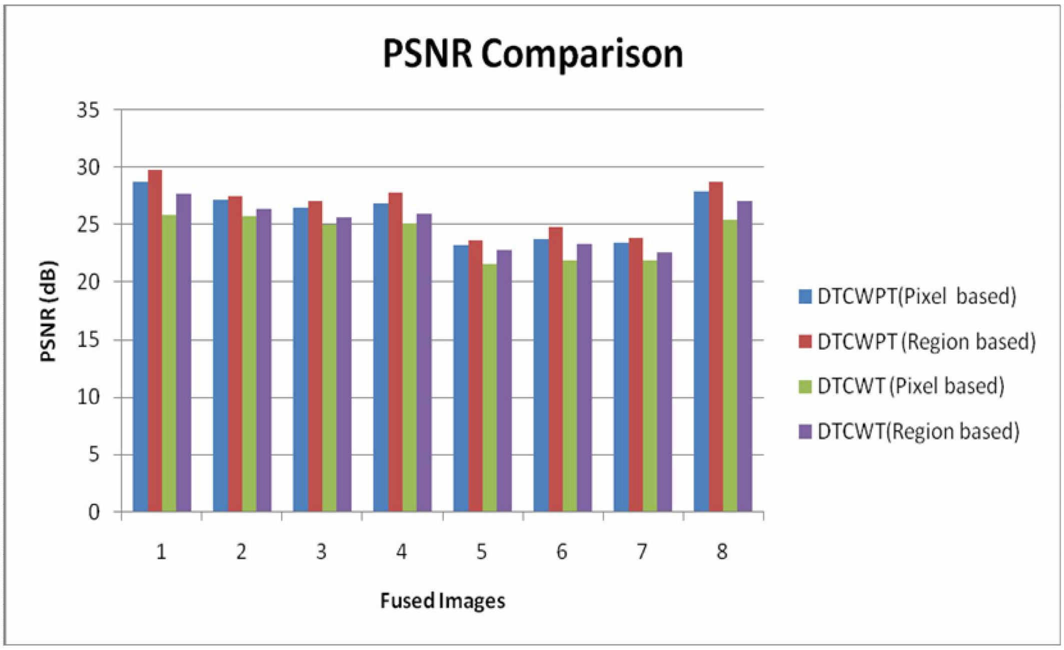

Figure 3.16 Overall PSNR comparison of pixel based and region based image fusion approaches

3.6.3.2 MSE comparison

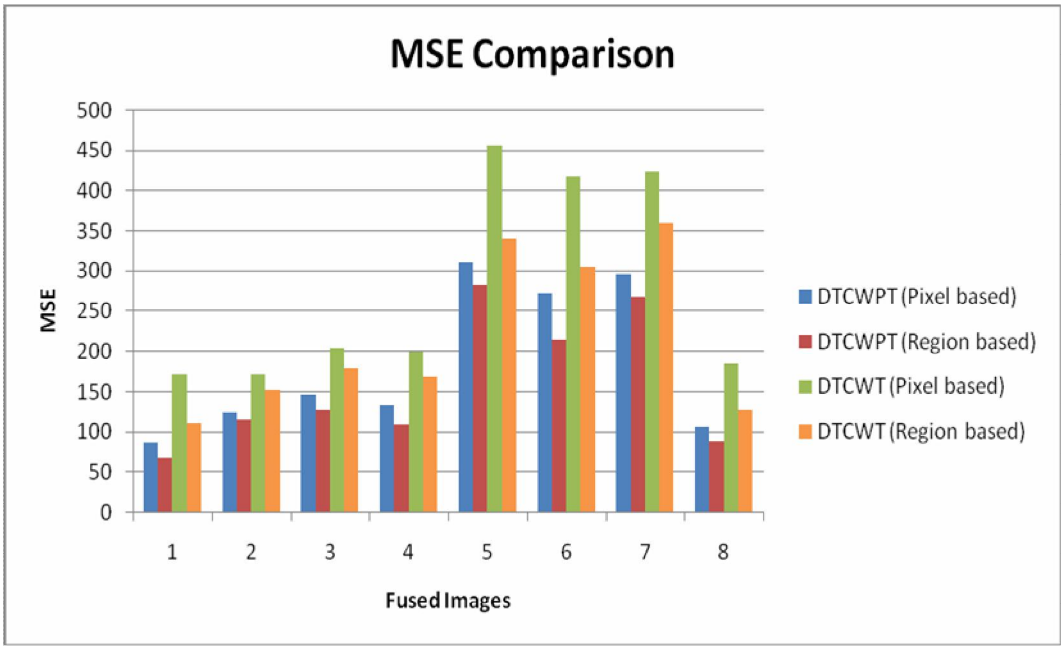

Figure 3.17 Overall MSE comparison for pixel based and region based image fusion approaches

Figure 3.16 and Figure 3.17 illustrate the overall performance comparison of pixel based and region based image fusion approaches in terms of PSNR and MSE respectively.

From the overall performance comparison based on simulation results between pixel based and region based image fusion approaches, the following noteworthy points are identified:

1) Pixel based image fusion using DTCWPT is superior to that of pixel based DTCWT approach.

2) Region based image fusion using DTCWPT outperforms the region based image fusion technique employing DTCWT.

3) Region based image fusion technique using DTCWT performs better than the pixel based approach using DTCWT.

4) Similarly, region based image fusion using DTCWPT is found to produce promising results compared to the pixel based approach utilising DTCWPT.

5) Region based image fusion supersedes the pixel based scheme and also, it is inferred that DTCWPT in image fusion is found to take over the place of DTCWT.

3.6.4 Histogram analysis

Histogram analysis for a particular example of medical imaging is considered. MR image (Figure 3.18) and CT image (Figure 3.19) are considered for histogram analysis. This analysis can be similarly carried out for other images also. Histogram gives a plot of gray level distribution vs. the number of pixels. It gives information about the number of pixels having a particular gray value, in an image. Entropy, which is the average information content, can be found from the normalised histogram. It can otherwise be found using the command available in MATLAB. The entropy values of the fused MR and CT output in pixel based DTCWPT image fusion and region based DTCWPT image fusion are found to be 5.99 pixels/gray value and 6.71 pixels/gray value respectively. Higher the entropy better is the fused output. The entropy values give a clear indication of region based fusion approach superseding the pixel based scheme.

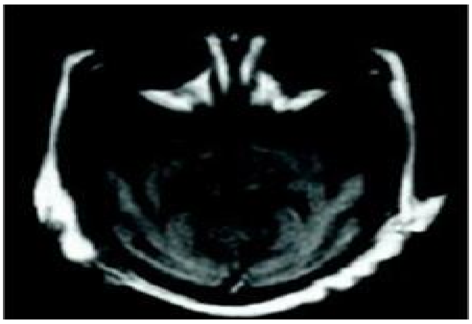

Figure 3.18 MR image

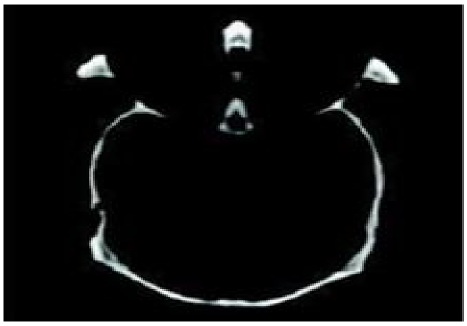

Figure 3.19 CT image

The gray values are considered to be distributed between 0 and 255. Black corresponds to 0 and white corresponds to 255. Intermediate gray shades are found between 0 and 255. The distribution of gray values of MR and CT images can be found from the histogram plots shown in Figure 3.20 and Figure 3.21 respectively.

3.6.4.1 MRI histogram

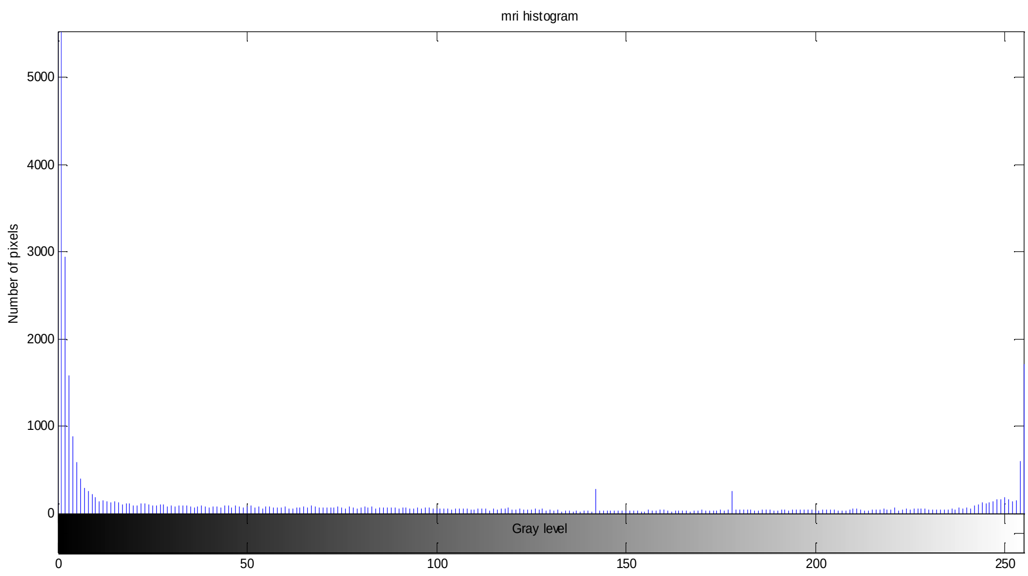

Figure 3.20 Histogram plot for MR image

3.6.4.2 CT histogram

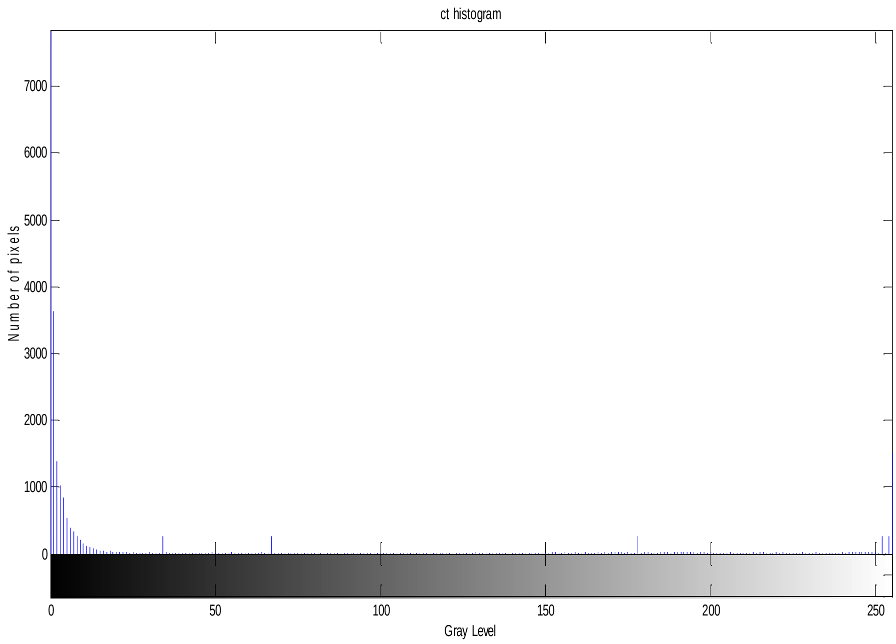

Figure 3.21 Histogram plot for CT image

The histograms for the fused MR and CT images corresponding to pixel based and region based image fusion approaches are shown in the subsequent plots.

3.6.4.3 Histograms of fused image

The histogram plots of fused medical image for pixel based and region based image fusion using DTCWPT are shown in Figure 3.22 and Figure 3.23 respectively.

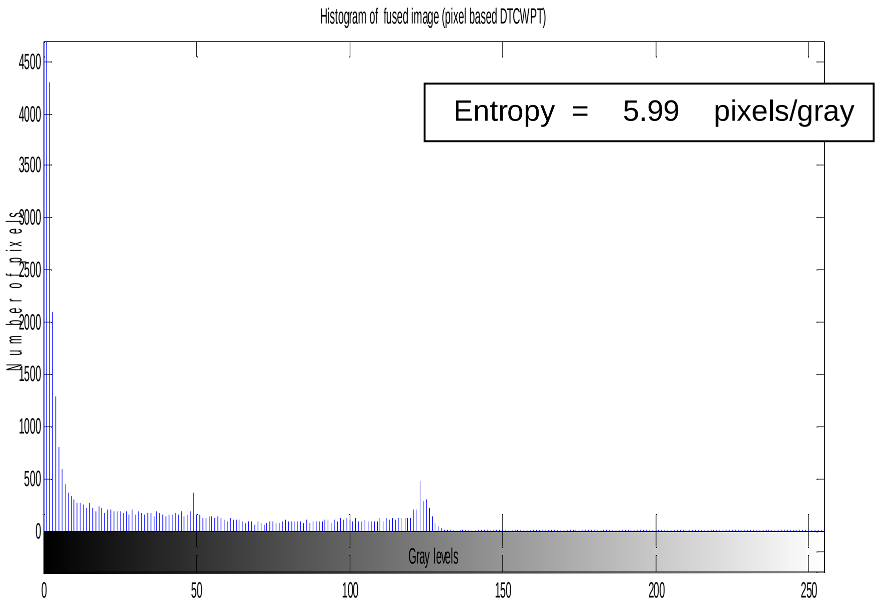

Figure 3.22 Histogram plot for fused image in pixel based image fusion approach

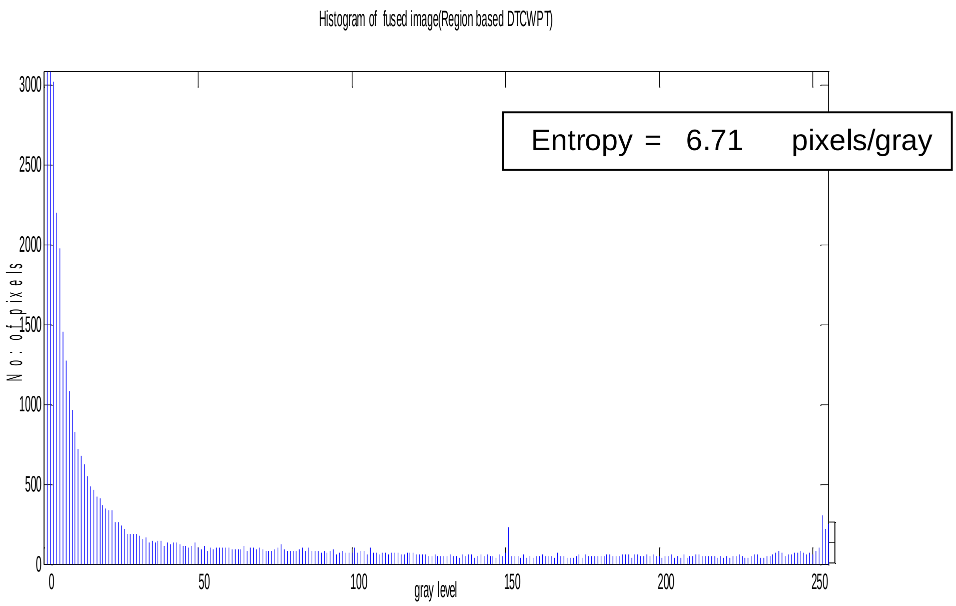

Figure 3.23 Histogram plot for fused image in region based image fusion approach

From the plots, it is inferred that region based image fusion using DTCWPT conveys higher average information content than pixel based scheme. It is yet another validation of region based scheme overriding the pixel based fusion.

3.7 CONCLUSION

Based on the simulation results, it is concluded that region based monochrome image fusion yields better results compared to that of the pixel based approach. It is effective in avoiding the problems such as the blurring effects, reduced contrast and sensitivity to noise in the output fused images. Eventhough it is difficult to differentiate visually small variations in gray values between both the approaches, quantitative analysis proves that region based approach performs well relatively. Segmentation plays an efficient role to achieve effective fusion. Since, colour conveys huge information and our eyes can discern even small variations in colour and can distinguish thousands of colours, next phase of the work is focussed on colour image fusion approach.

CHAPTER 4

PIXEL BASED AND REGION BASED COLOUR IMAGE FUSION USING DTCWPT

4.1 INTRODUCTION

Most of the image fusion work has been limited to monochrome images. Of late, algorithms which utilize human colour perception are attracting the image fusion community with great interest. It is mainly due to the reason that the use of colour greatly expands the amount of information to be conveyed in an image. Since, the human visual system is very much sensitive to colours, research was undertaken in mapping three individual monochrome multispectral images to the respective channels of an RGB image to produce a false colour fused image. Producing a fused colour output image which maintains the original chromaticity of the input visual image is highly tricky. A successful multisensor colour image fusion scheme is the one which preserves the salient information present in the visual colour image and the IR image. It should also be efficient enough to preserve the chromaticity of the visual image in the fused output.

Fusion of colour image and an IR image represented in gray scale cannot be done directly, since both the images considered for fusing should be of the same type. This necessitates the conversion of RGB image to HSI format. It is then followed by the fusion of intensity components of colour image with the IR image. Finally, the hue and saturation components are added with the new intensity components of fused output, thereby the colour output is obtained. To get the colour fused image in RGB format, the fused HSI output is converted back to RGB format.

An RGB colour image is given by an M X N X 3 array of colour pixels, where each pixel is a triplet corresponding to the red, green and blue components of an RGB image at a specified location. In HSI colour space, the hue component represents the dominant colour present in an image. The saturation component indicates the amount of purity. The intensity component gives the gray level values of the image. The HSI colour system is considerably closer than the RGB system to human perception in describing the colour sensations. Further, HSI colour space allows the de-coupling of intensity component from the colour carrying information in an image. Hence HSI colour space is used for intermediate processing in an image fusion task.

Colour image fusion is carried out using DTCWPT, which is characterized by rich features compared to DTCWT. Simulation for fusing the input images (visual colour image and IR image) is carried out using MATLAB programming. Both pixel based and region based approaches are attempted for colour image fusion. The output obtained in both these approaches are compared qualitatively. Further, quantitative comparison is done by using entropy and UIQI as performance metrics.

4.2 PIXEL BASED COLOUR IMAGE FUSION

Pixel based image fusion of monochrome and IR images has already been dealt in depth in chapter 2 and is extended for colour image fusion in this chapter.

The pixel based approach for colour image fusion is summarized in step1 to step 5:

1) If a colour image is to be fused with an IR image , the preliminary step requires the conversion of RGB colour information to HSI components. It is followed by the application of DTCWPT to the intensity components of colour image and IR image respectively.

2) The maximum selection rule is applied to find the largest absolute wavelet coefficients at each location of the input images to produce a single set of coefficients in the fused image

3) Inverse DTCWPT is applied to get the final fused output in spatial domain

4) Now, the Hue and Saturation components are added to the intensity image to get the final fused colour image.

5) Finally, the HSI colour space is converted to RGB format

4.2.1 Flowchart for pixel based colour image fusion

As enumerated earlier in monochrome image fusion, in pixel based colour image fusion approach, the fusion decision is based on maximum selection rule. The wavelet coefficients of the two images are compared on a one-to-one basis and whichever coefficients are having the maximum absolute value of the two images, those are taken into account in the fused image. Other coefficients are omitted.

The steps involved in pixel based colour image fusion can be represented diagrammatically in Figure 4.1

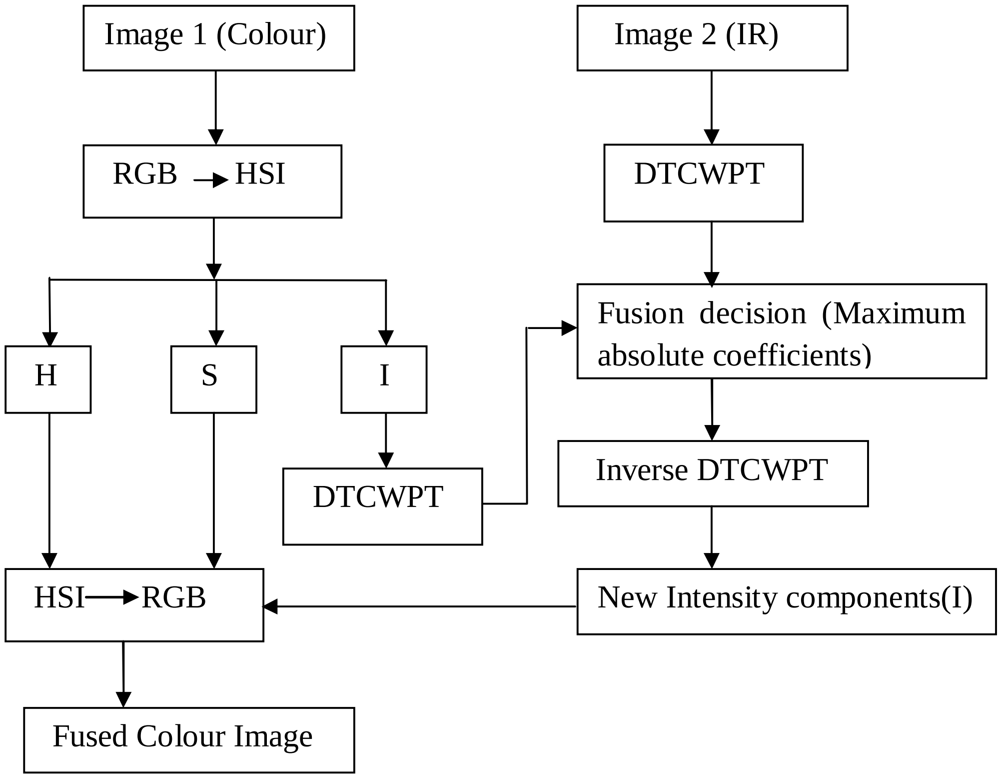

Figure 4.1 Flowchart indicating the steps involved in pixel based colour image fusion using DTCWPT

4.3 REGION BASED COLOUR IMAGE FUSION

In this approach, as already been discussed in chapter 3, segmentation plays a vital role in determining the effective fusion strategy. Effective fusion in region based technique mainly depends on efficient segmentation. Fuzzy based technique is employed to achieve an efficient segmentation. It is followed by statistical region merging to fine tune the segmentation process. The statistical parameters are considered for region merging. Here, the statistical parameter, the mean intensity difference between the adjacent regions is considered. If it is lesser, the adjacent regions are merged together into a single region. It is followed by image fusion step. The two images to be fused should be of same type. As discussed earlier, only the intensity components of the two images are considered initially and finally the hue and saturation components are added .The HSI image is converted to RGB image to get the final fused output in spatial domain.

The steps involved in region based fusion scheme (colour and IR image) are summarized as follows:

1) The RGB components of colour image (Image 1) are converted to HSI components.

2) DTCWPT is applied to intensity image 1 and IR image 2 respectively

3) Region based segmentation using fuzzy clustering is carried out to segment the regions in image 1 and image 2.

4) Fusion decision is taken based on the region features of image 1 and image 2

5) The approximate images are combined in transform domain

6) Inverse DTCWPT is taken to get the fused image in the spatial domain

7) The hue and saturation components are added to the fused intensity image to get the final fused colour image

4.3.1 Flowchart for region based colour image fusion

Figure 4.2 depicts the steps involved in region based colour image fusion using DTCWPT.

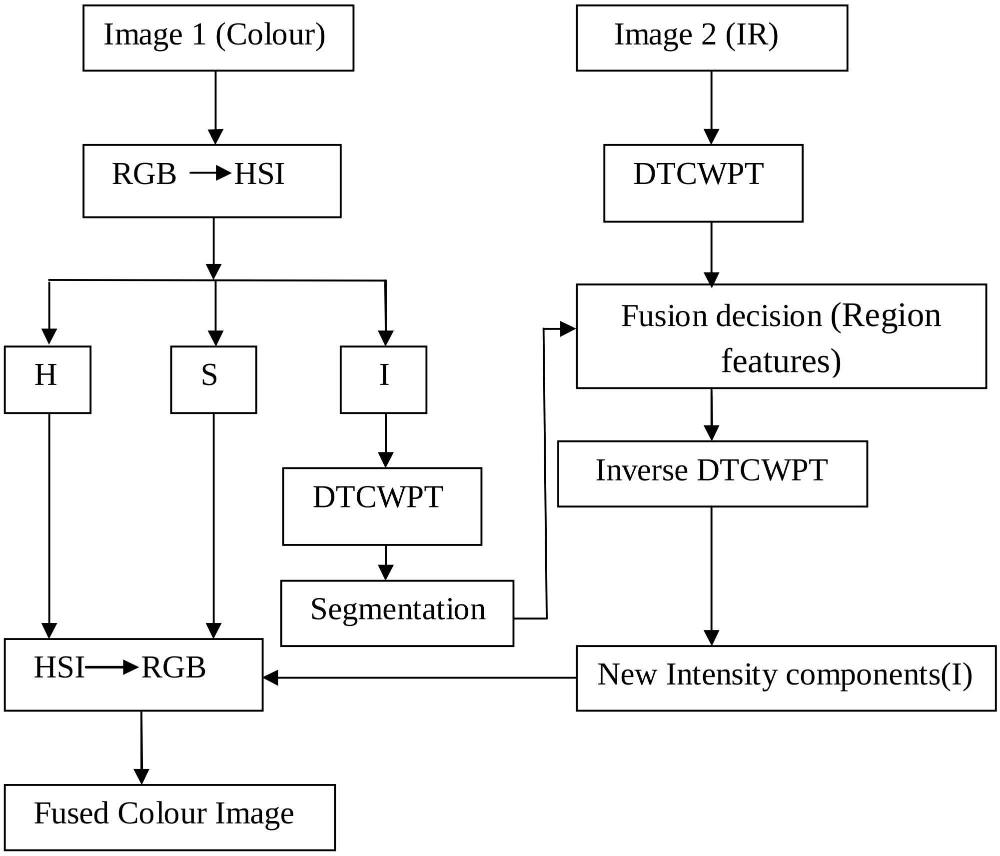

Figure 4.2 Flowchart indicating the steps involved in region based colour image fusion using DTCWPT

4.4 RESULTS AND DISCUSSION

4.4.1 Qualitative performance comparison

EXAMPLE 1

Concealed weapon detection (CWD) is an important topic of interest in controlling the untoward incidents in the area of law enforcement. In this example, concealed weapon is detected by the fusion of visual colour image of a person shown in Figure 4.3(a) and the corresponding IR image in Figure 4.4(a). The input images considered for fusion are taken from [112]. The resolution of the visual colour image (Figure 4.3(a)) is much higher than that of the IR image shown in Figure 4.4(a). But, the visual image does not convey any information about the concealed weapon.

The resolution of the IR image is poorer, but the concealed weapon could be located in this image. The body appears to be brighter than the background in this image. Further, the background is almost black and shows only a little detail because of the high thermal emissivity of the body. The weapon is darker than the surrounding body due to the temperature difference between it and the body. On fusing these two images, the exact identity of the person along with the location of the concealed weapon could be identified with better clarity.

The important intermediate processes to be considered for each image in region based colour image fusion scheme are filtering followed by binary segmentation, multiscale segmentation and statistical region merging which are same as that dealt in chapter 3. The output corresponding to these steps for the input colour image are shown in Figure 4.3(b) , Figure 4.3(c) and Figure 4.3(d) respectively. The output corresponding to the intermediate processes for IR image are shown in Figure 4.4(b), Figure 4.4(c) and Figure 4.4(d) respectively.

Figure 4.3(a) Input colour image [112]

Figure 4.3(b)
Filtered binary image

Figure 4.3(c)
Multiscale segmentation

Figure 4.3(d)
After Statistical region merging

Figure 4.3 Segmented output of input colour image of EXAMPLE 1

Figure 4.4(a) Input IR image

Figure 4.4(b)
Filtered binary image

Figure 4.4(c)
Multiscale segmentation

Figure 4.4(d)
After Statistical region merging

Figure 4.4 Segmented output of input IR image of EXAMPLE 1

The input colour image (Figure 4.5(a)), which is same as that of Figure 4.3(a) and IR image (Figure 4.5(b)), which is same as that of Figure 4.4(a) are fused to produce pixel based fused output and region based fused output respectively as shown in Figure 4.5(c) and Figure 4.5(d) respectively.

Figure 4.5(a)

Image 1 (Visual)

Figure 4.5(b)

Image 2 (IR)

Figure 4.5(c) Fused Output

(Pixel based DTCWPT)

Figure 4.5(d) Fused Output

(Region based DTCWPT)

Figure 4.5 Pixel based and region based fused output (colour) using DTCWPT for EXAMPLE 1

The fused output of both the approaches reveal the information content present in the visual image and in the IR image. The identity of the person with the concealed weapon could be visualized in the fused output. But, the fused output of region based approach surpasses the pixel based output in maintaining the chromaticity of the visual image and in better identification of the person.

EXAMPLE 2

Figure 4.6(a)
Input colour image 1

Figure 4.6(b)
Input image 2

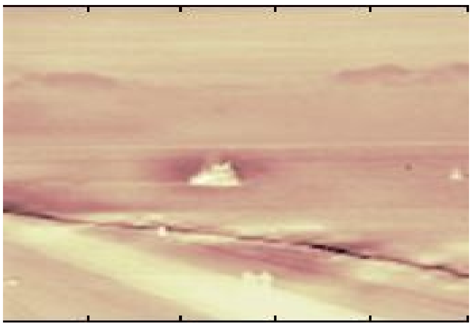

Figure 4.6 (c) Fused output (Pixel based DTCWPT)

Figure 4.6(d) Fused output (Region based DTCWPT)

Figure 4.6 Pixel based and region based fused output (colour) using DTCWPT for EXAMPLE 2

In this example, the fused output preserves the information contained in the input images. Figure 4.6(a) is the input colour image which is fused with the image shown in Figure 4.6(b). The chromaticity of the output is more or less the same as that of the input colour image 1. Further, the path of the seashore and the persons seen in input image 2 are also visible in the fused output. The fused output corresponding to pixel based image fusion using DTCWPT is shown in Figure 4.6(c) and the output corresponding to region based approach can be seen in Figure 4.6(d). Better details can be visualised in the fused output of Figure 4.6(d) corresponding to region based approach.

EXAMPLE 3

Figure 4.7(a) Input colour Image

Figure 4.7(b) Input IR Image

Figure 4.7(c) Fused output (Pixel based DTCWPT)

Figure 4.7(d) Fused output (Region based DTCWPT)

Figure 4.7 Pixel **based and region based fused output (colour) using DTCWPT for EXAMPLE 3**

In this example, the visual sensor could not capture the image of a person (Figure 4.7(a)) , whereas the IR image of Figure 4.7(b) shown reveals the person standing in the bush. On fusing these two images, the chromaticity of the colour image in Figure 4.7(a) along with the person visible in the IR image could be identified in the fused output. The region based fused output of Figure 4.7(d) is found to be better compared to that of the pixel based output of Figure 4.7(c).

In pixel based approach, the wavelet coefficients of the two input images are compared on a one-to-one basis and those coefficients which have the maximum absolute values are only considered in the fused output. The remaining coefficients are left out because of which the the intensity components get affected and the information content gets lost. The intensity components are one of the deciding factors of the overall HSI output. Since, the intensity components get affected in pixel based approach, chromaticity also gets affected. Therefore, in all the examples shown, one could find that the chromaticity of the original input image is getting affected in the pixel based approach whereas, region based output seems to be appealing in all the cases. Further, the pixel based technique is vulnerable to noise and may sometimes result in a blurred output.

EXAMPLE 4

Figure 4.8(a) Input colour image

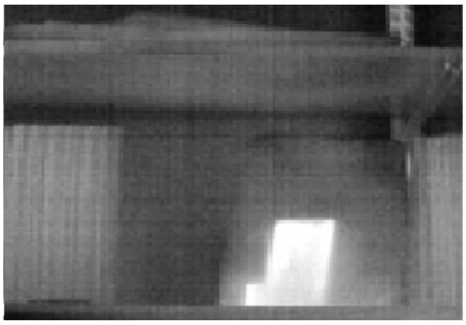

Figure 4.8(b) Input IR image

Figure 4.8(c) Fused output (Pixel based DTCWPT)

Figure 4.8(d) Fused output (Region based DTCWPT)

Figure 4.8 Pixel based and region based fused output (colour) using DTCWPT for EXAMPLE 4

In this example, the fused output is found to possess the features present in both the input images. The information content of the visual image shown in Figure 4.8(a) along with the concealed object seen in the IR image of Figure 4.8(b) are present in the fused output. Pixel based and Region based fused output are shown in Figure 4.8(c) and Figure 4.8(d) respectively.

In all the examples shown, region based fusion seems to outperform the pixel based colour image fusion due to the reasons already enumerated in example 3.

4.4.2 Quantitative performance comparison

Performance analysis based on the metrics of entropy and UIQI is an added validation to justify the superior performance of region based colour image fusion over that of the pixel based approach. Entropy comparison is done for both the pixel based and region based approaches by considering five fused images as seen in Figure 4.9. Entropy gives the average information content present in an image. Higher the entropy, better is the fused output.

Region based approach supersedes the pixel based approach in terms of entropy, as seen from the chart below. It is also evident from the visual quality of the fused output.

4.4.2.1 Entropy comparison

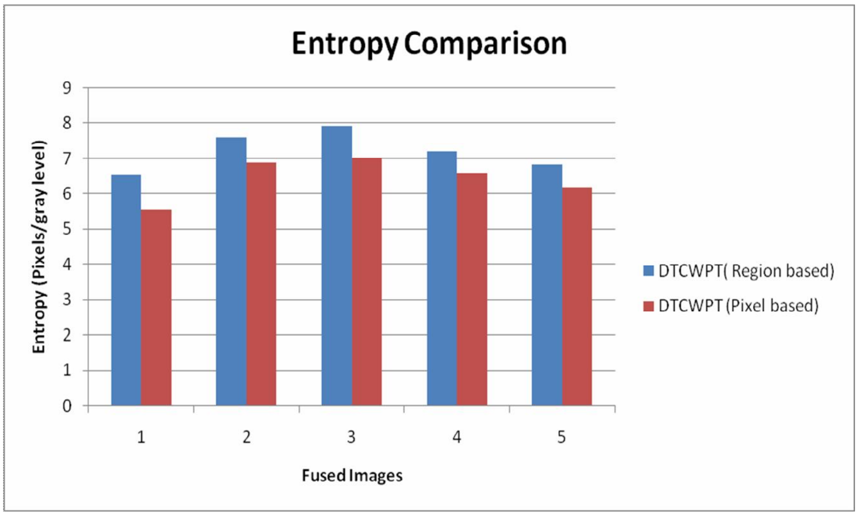

Figure 4.9 Entropy comparison for fused colour images in region based and pixel based approaches

4.4.2.2 Universal Image Quality Index (UIQI)

Another metric chosen for comparison is UIQI given by,

$$Q = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \frac{2\overline{x}.\overline{y}}{(\overline{x})^2 + (\overline{y})^2} \frac{2\sigma_x \sigma_y}{\sigma_x^2 + \sigma_y^2} \qquad (4.1)$$

where, $\overline{x} = \frac{1}{N_t} \sum_{i=1}^{N} x_i$, $\overline{y} = \frac{1}{N_t} \sum_{i=1}^{N} y_i$, $\sigma_{xy} = \left(\frac{1}{N_t - 1} \right) \sum_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})$,

$$\sigma_x{}^2 = \left(\frac{1}{N_t - 1}\right)\sum_{i=1}^{N}(x_i - \bar{x})^2 \quad \text{and} \quad \sigma_y{}^2 = \left(\frac{1}{N_t - 1}\right)\sum_{i=1}^{N}(y_i - \bar{y})^2 \ .$$

'x' and 'y' correspond to the images to be fused.

N_t - Total number of pixels in the image

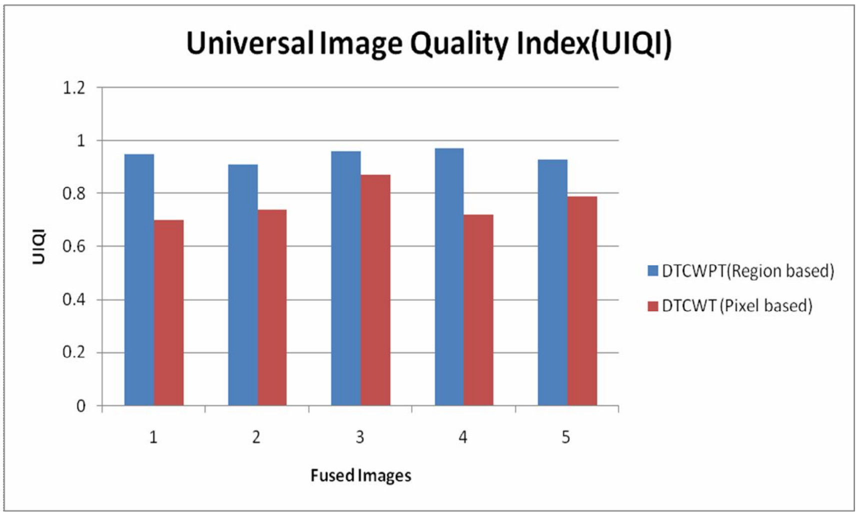

Figure 4.10 Comparison of UIQI for fused images in region based and pixel based approaches

The first component in the expression for Q is the correlation coefficient between x and y. The second component measures the closeness of the mean luminance between x and y. The third component measures the similarity of contrast between the two images. An UIQI value closer to unity represents better match of the fused output with the input. It is evident from Figure 4.10, that region based fused output has better matching with the input than the pixel based counterpart.

4.5 CONCLUSION

The performance of colour image and IR image fusion using DTCWPT is found to be better in region based approach compared to that of the pixel based technique. Further work is focussed on watermarking the fused medical image in wavelet domain for telemedicine applications.

CHAPTER 5

WATERMARKING FUSED IMAGE FOR TELEMEDICINE APPLICATIONS

5.1 INTRODUCTION

The advent of internet has resulted in great opportunities for the creation and delivery of content in digital form. Applications include electronic advertising, real time audio and video delivery, web publishing etc., An important issue that arises in all these applications is the protection of the rights of all the participants. There is a fair chance of meddling with the transmitted data and authenticity of transmitted information becomes questionable [2]. Modern health care service is based on digital information management. Although, recent advancements in information and communication technologies provide new means to access, handle and move medical images, they also allow easy manipulation and replication. This demands the need for security measures in medical information system. One such security measure to deter the practice of manipulation of information content is based on digital watermarking techniques. These techniques are deemed essential to address some of the challenges posed by the rapid proliferation of the digital content.

A digital watermark can be described as a visible or preferably an invisible identification code that is permanently embedded in the data. A general definition can be given as: “Hiding of a secret message or information within an ordinary message and extraction of it at its destination.” The goal is to embed some information in the image without affecting its visual content. Invisible watermark embedded in an image poses a great challenge for the attackers and is highly difficult to tamper with. It also guarantees the authentication of the transmitted data in telemedicine applications.

5.2 APPLICATIONS

Digital watermarking is considered as an imperceptible, robust and secure communication of data related to the host signal, which includes embedding into and extraction from the host signal. Some applications of invisible watermark are listed below:

Fingerprinting: When multimedia content is distributed over a network, there is a chance of illegal duplication and distribution of the data transmitted. Hence, a unique watermark is embedded in each copy of the data to avoid such malpractice [52]. In case of an unauthorised distribution, retrieval of fingerprint would help in locating such irregularities.

Copy prevention or control: Watermarks can also be used for copy prevention and control. For example, where the multimedia content needs special hardware for copying and/or viewing, a digital watermark can be inserted indicating the number of copies that are permitted. Every time a copy is made, the watermark can be modified by the hardware and after a point, the hardware stops creating further copies of the data. An example of such a system is Digital Versatile Disc (DVD).

Fraud and tamper detection: When multimedia content is used for legal purposes, medical applications, news reporting and commercial transactions, it is important to ensure that the original source content has not been changed, manipulated or replicated. This can be ensured by embedding a watermark in the data. The integrity of data is verified by the integrity of the extracted watermark.

Apart from these, there are other applications such as indexing, broadcast monitoring, owner identification , data hiding, medical safety etc., In this chapter, watermarking is applied to a fused medical image and is considered for telemedicine applications. This ensures the authenticity and integrity of medical records.

5.3 IMAGE FUSION WITH DTCWPT

In wavelet based watermarking, DTCWT [107,108] has been considered to be an effective domain for embedding imperceptible and robust watermarks, so far. Since DTCWPT has desirable features over DTCWT, watermark embedding and extraction using DTCWPT are considered in this chapter. As explained already in earlier chapters, fusion of MR and CT images is carried out using DTCWPT. The fused medical image is considered for telemedicine applications. Since, there is a chance of manipulating or replicating the data transmitted, the fused medical image in the transform domain needs to be invisibly watermarked by embedding the patient's information in the wavelet coefficients. The watermark is then extracted by the authenticated person and the fused medical image is also recovered at the receiving end.

An MR image can highlight a higher detail in soft tissues and can produce a detailed image of tissues and brain. Unlike MRI, a CT image can outline the bony structures inside the body very accurately. Fusing MR and CT images of a patient helps in better medical diagnosis. Tumour visualization is difficult using CT alone. Therefore, treatment planning based on fused CT and

MR data enables better definition of target volume and critical structures than based on CT alone.

Fusion algorithm is the initial step to be implemented. Region based image fusion is carried out initially before embedding the watermark. This algorithm comprises of the following steps. Initially, each of the two images, i.e., CT and MR images is filtered and binary segmented. A multiscale segmentation is then applied to the resulting regions, according to the local texture characteristics. A small window size of 3x3 is used to localise the intensity in homogeneous regions. A window size of 7x7 is considered, when a large intensity variation is encountered. It is followed by statistical region merging. The pair of regions with the minimum distance is merged until a maximum threshold of the distance is reached. A suggested value found experimentally for the threshold is 0.4 for natural images and 0.6 for multimodal images [37].The fused image is generated by using the weighted combination of the two images.

5.4 WATERMARKING FUSED IMAGE

Image fusion is followed by watermark embedding stage. The general Block Diagram for watermark embedding and extraction is shown in Figure 5.1. The gray scale fused image is decomposed using DTCWPT. One level of decomposition is considered to reduce the complexity. The fused CT and MR image is watermarked by embedding a logo containing the patient information in the LL plane (in order to achieve robust watermarking) of DTCWPT for telemedicine applications. The watermark being added is a small grayscale image compared to the size of the fused image.

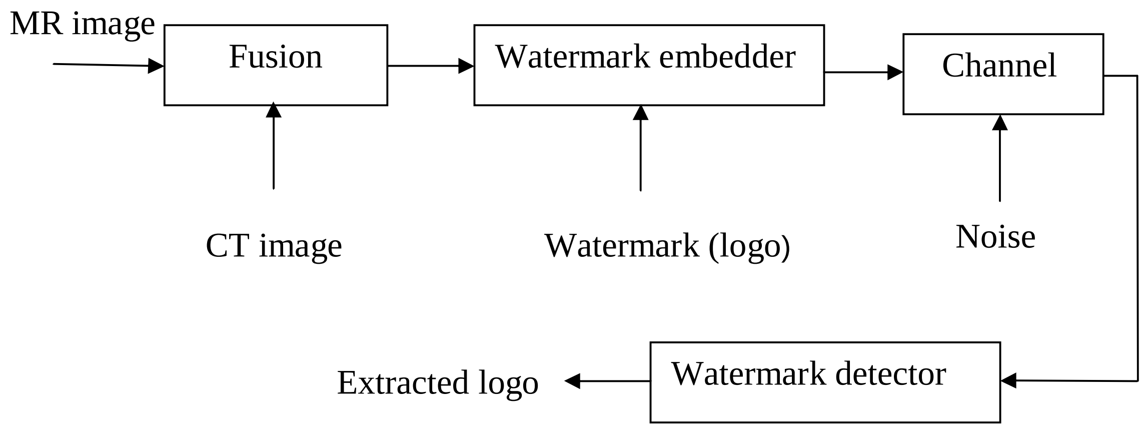

Figure 5.1 General Block Diagram for watermark embedding and extraction

The watermark is resized to that of the LL plane. A scaling factor less than unity is chosen before embedding the logo in the LL plane. Then the logo is embedded in the LL plane of the host image. The watermark being added is invisible. The host image containing the logo with manipulated coefficients yields the watermarked image. When this image is to be transmitted from one end to the other for telemedicine applications, there is a higher probability of the image being corrupted by noise. Hence, impulse noise is added intentionally and filtered out using the filter as described in [62].

Filtering performance is also tested using Feed forward Neural Network by applying the Back Propagation Algorithm [64]. Neural Network is trained at 50% noise using two hidden layers with 15 neurons each and the testing is done at different percentages of noise levels, to achieve a target error of 0.0001. To achieve this target, a total of 3000 iterations were required, which consumed three hours of training time Two input images comprising 1,23,072 data points were considered for training. The PSNR values and RMSE values of filtered output for 20% added noise are shown. The filtered watermarked image is subjected to DTCWPT and the watermark key is subtracted from the LL coefficients of the received watermarked image. By performing the inverse transformation, watermark is extracted. This assures the authenticity of medical information in telemedicine applications.

5.5 RESULTS AND DISCUSSION

5.5.1 Qualitative performance comparison

The CT image shown in Figure 5.2 is fused with the MR image of Figure 5.3 to yield the fused output shown in Figure 5.4. The watermark or the logo is the patient information shown in Figure 5.5 to be hidden in Figure 5.4. Figure 5.6 represents the Low-Low (LL) plane in which the logo is embedded. The fused image with the embedded logo in LL plane is shown in Figure 5.7. The logo is scaled by a scaling factor of less than unity, such that it is made invisible. If the scaling factor is chosen higher, the embedded logo is made visible, as can be seen from Figure 5.8. It is better to embed a logo such that it is invisible, so that tampering task becomes tricky. Figure 5.9 shows the watermarked image, which gets corrupted by noise on transmission and the noise corrupted image, is shown in Figure 5.10. The image obtained after the removal of noise is given in Figure 5.11. The recovered image and the extracted logo are given by Figure 5.12 and Figure 5.13 respectively.

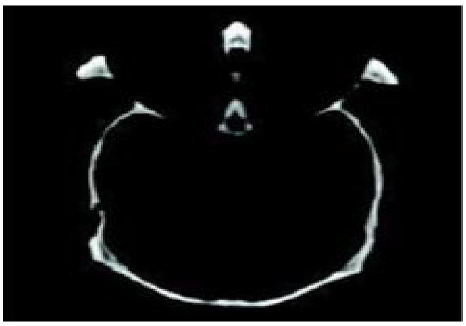

Figure 5.2 Input medical Image 1 (CT)

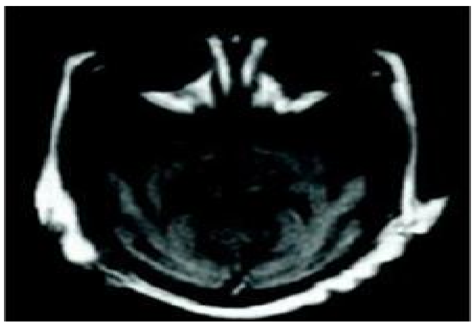

Figure 5.3 Input medical image 2 (MR)

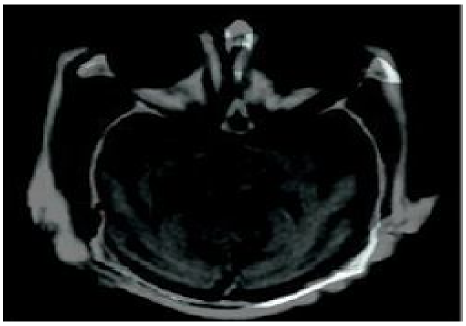

Figure 5.4 Fused output (DTCWPT)

Figure 5.5 Watermark (logo)

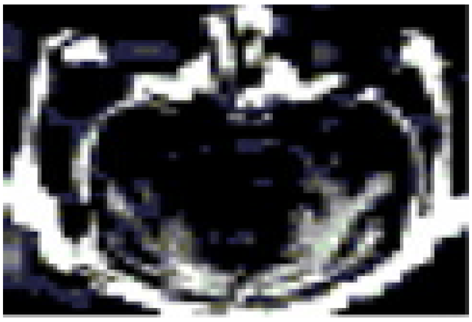

Figure 5.6 LL plane

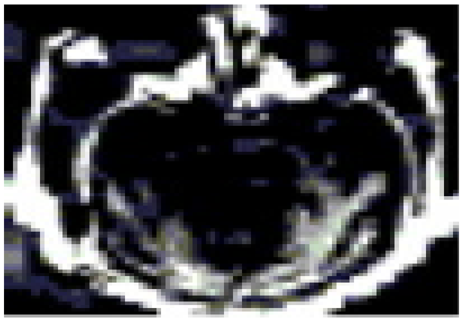

Figure 5.7 LL pane with an invisible logo

Figure 5.8 LL plane with logo made visible

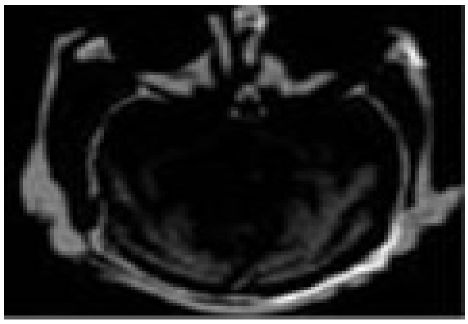

Figure 5.9 Watermarked image

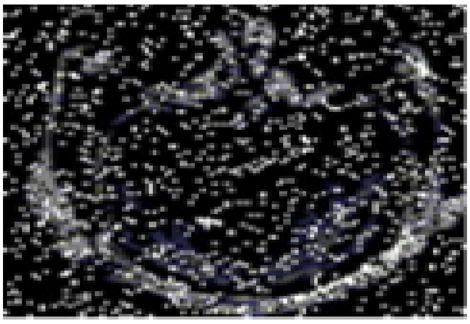

Figure 5.10 Noisy image

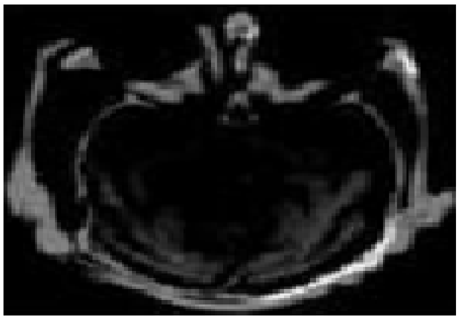

Figure 5.11 Filtered image

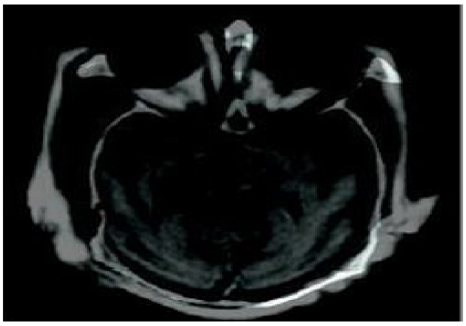

Figure 5.12 Extracted image

Figure 5.13 Extracted logo

5.5.2 Quantitative performance comparison

The performance of DTCWT and DTCWPT when applied for watermarking applications of fused medical image is evaluated based on MSE, PSNR and Normalised Cross Correlation. This comparison can be found in Table 5.1. It s found that DTCWPT performs better compared to DTCWT.

TABLE 5.1 Performance comparison of wavelet based watermarking techniques

PARAMETERS	DTCWT	DTCWPT
PSNR (dB)	24.2	28.5
MSE	247.21	91.85
Normalised Cross Correlation	0.956	0.996

Higher the PSNR value lower is the MSE and hence, better is the performance.

Normalised Correlation (NC) is used to judge the similarity between two images. If this value is closer to unity, the two images are similar.

$$NC = \left\{ \sum_{i=1}^{M}\sum_{j=1}^{N} W(i,j)W'(i,j) \Big/ \sum_{i=1}^{M}\sum_{j=1}^{N}\left(W(i,j)\right)^2 \right\} \quad (5.1)$$

If the size of the image is MxN, the variable 'i' in the summation runs from 1 to M and 'j' runs from 1 to N.

W (i , j) – watermark used for embedding

W’ (i , j) – retrieved watermark

5.6 CONCLUSION

Watermarking of fused medical image ensures security in digital transmission of information. Invisible watermarking is done to ensure that tampering becomes a difficult job. Noise removal is also carried out, and the watermark and the image are extracted successfully at the receiving end. A comparison between the DTCWT and DTCWPT based watermarking techniques is carried out. From the quantitative comparisons based on PSNR, MSE and NC, it is evident that DTCWPT performs better than DTCWT in watermarking applications.

CHAPTER 6

SEGMENTATION OF FUSED IMAGE

6.1 INTRODUCTION

Extracting information from an image is referred to as image analysis. Image segmentation is an essential preliminary step in most automatic pictorial pattern recognition and scene analysis problems. It is one of the most difficult tasks in image processing. It is the process of partitioning a digital image into multiple regions or clusters, used for locating objects of interest and boundaries like lines and curves in an image. Each region is made up of sets of pixels. The fused image finds applications in further image processing tasks such as segmentation, feature extraction , machine object recognition etc.,

The requirements of good colour image segmentation are as follows: A single region in a segmented image should not contain significantly different colours and a connected region containing the same colour should not have more than one label. All significant pixels should belong to the same labelled region. The intensity of a region should be reasonably uniform. Colour image segmentation is useful in many applications. From the segmentation results, it is possible to identify clearly the regions of interest and objects in the scene, which helps in subsequent image analysis. Fuzzy based techniques have gained increasing popularity in the field of colour image segmentation.

The method proposed here does not require prior knowledge about the number of objects in an image and calculates the threshold value automatically required for segmentation. Segmentation of fused colour image is considered, which combines the aspects of FCM and A-IFS techniques to achieve better performance. This method calculates membership values using FCM and uses A-IFS histon for calculating the number of clusters and finally, it employs roughness index to get optimum threshold values for segmentation.

6.2 BLOCK DIAGRAM OF THE PROPOSED METHOD

The Block Diagram of the proposed method which merges FCM algorithm with the A-IFS histon approach is as shown in Figure 6.1.

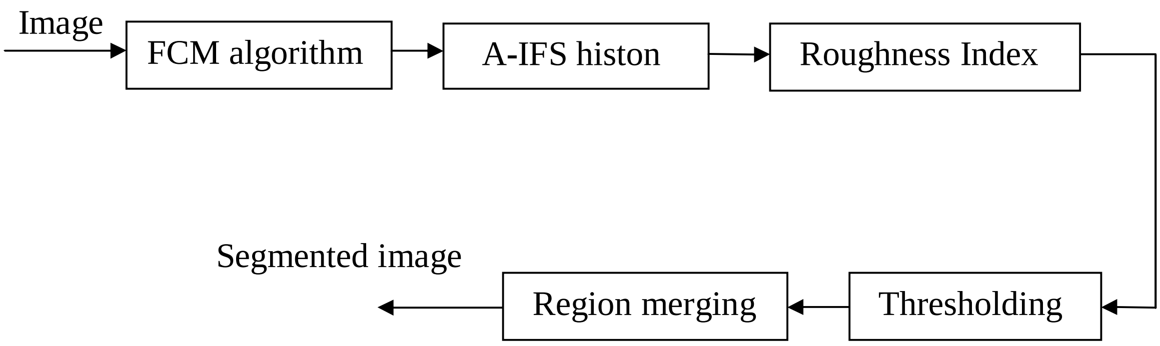

Figure 6.1 Block Diagram of the proposed segmentation method

FCM algorithm is applied to find the membership values as described in the previous section. The non-membership values and the roughness index are found out using A-IFS histon method. Roughness index is used as a means for segregating the regions. Finally, region merging is done to achieve better region based segmentation depending on colour.

6.3 FUSION OF A-IFS HISTON AND FCM TECHNIQUES

Digital images are always characterised by inherent vagueness or imprecision of gray values of the pixels and this kind of fuzziness can also be observed in region boundaries, where it would be highly difficult to have a clear demarcation of edges. Clustering techniques based on FCM have been widely used to deal with such ambiguities. Intuitionistic fuzzy set theory is one of the popular techniques being employed in image processing wherein intuitive ways are used to describe the inherent ambiguity present in images. Intuitionistic fuzzy sets proposed by Atanassov are best suited for modelling the hesitancy arising out of the imprecise information. These are defined by two characteristic functions, namely the membership function and non-membership function. Membership function gives a degree of belongingness of an element to the universe of IFS and non-membership function gives the degree of non-belongingness. The A-IFS representation of images is given by,

$$I=\{(g_{ij},\mu_I(g_{ij}),\nu_I(g_{ij}))\},\ i=1,\ldots,M;\ j=1,\ldots,N \tag{6.1}$$

g_{ij} - gray values in an image of size M X N

$\mu_I(g_{ij})$ – degree of membership

$\nu_I(g_{ij})$ – degree of non-membership

The membership value at each pixel location is given by the normalised intensity values [80] . The proposed approach differs from [80] in the calculation of membership values alone. In the proposed technique, FCM algorithm [70] is applied to find the membership values instead of using normalised intensity values as in [80].

The membership values using FCM algorithm are determined as follows:

1. An image ‘I’ of size p x q with ‘n’ number of clusters is considered for analysis.

$$I = \begin{bmatrix} (c1, c2, c3)_{(1\times1)} & \cdots & (c1, c2, c3)_{(1\times q)} \\ \vdots & \ddots & \vdots \\ (c1, c2, c3)_{(p\times1)} & \cdots & (c1, c2, c3)_{(p\times q)} \end{bmatrix}$$

(6.2)

2. The objective function, J_{FCM} of the image ‘I’ is first initialized to zero,

$$J_{FCM}(0)=0 \tag{6.3}$$

3. A matrix ‘U’ is used to store the membership functions ‘$\mu_{x,i}$’ corresponding to each pixel value.

$$U=\begin{bmatrix} (\mu)_{(1,1)}(\mu)_{(2,1)} & \cdots & (\mu)_{(n,1)} \\ \vdots & \ddots & \vdots \\ (\mu)_{(1,c)}(\mu)_{(2,c)} & \cdots & (\mu)_{(n,c)} \end{bmatrix} \tag{6.4}$$

4. The centre ‘ϑ_i’ of each cluster containing the membership values of each pixel is given by,

$$\vartheta_i = \frac{\sum_{x=1}^{N} \mu_{x,i}^{m} Z_x}{\sum_{x=1}^{N} \mu_{x,i}^{m}} \tag{6.5}$$

where ν_i(i=1,2,…, c) is the centre of each cluster, $\mu_{(x,i)}$ (x=1,2,…, n, i=1,2,…, c) is membership value and $Z_x = (c_1,c_2,c_3)_x$, (x=1,2,…, n) is the pixel value and ‘m’ is fuzzification parameter which is usually taken as 2 for soft clustering.

5. The distance equation to find the distance‘d’ from the centre of the cluster to

each pixel is given by,

$$d^2(Z_x,\nu_i)=||Z_x-\nu_i||^2 \quad (6.6)$$

6. Using the membership values and Euclidean distance, the objective function is calculated by,

$$J_{FCM}(r) = \sum_{i=1}^{N}\sum_{i=1}^{c}\mu_{x,i}^{m}d^2(Z_x,\vartheta_i) \quad (6.7)$$

where, ‘r’ is the present no. of iterations.

7. The difference between the present objective function and previous objective function is found by,

$$\text{Difference}=J_{FCM}(r)–J_{FCM}(r-1) \quad (6.8)$$

8. When this difference is less than the threshold value of 0.00001, clustering is stopped. This threshold value has been chosen after making an extensive study on a number of images, for terminating the iteration. A threshold of higher value than this resulted in improper clustering for some images. When the difference is more than the threshold value, the next iteration takes place starting from step 4. The new membership function for next iteration is given by,

$$\mu_{x,i} = \frac{\left(\frac{1}{d^2(Z_x,J_i)}\right)^{\frac{i}{(m-1)}}}{\sum_{i=1}^{c}\left(\frac{1}{d^2(Z_x,J_i)}\right)^{\frac{1}{(m-1)}}} \quad (6.9)$$

9.The average intensity of the pixels is given by,

$$\mu_I^a\left(g_{ij}\right)=\sum_{k=-1}^{1}\sum_{l=-1}^{1}\mu_I(g_{(i+k)(j+l)}h(i+k,j+l) \tag{6.10}$$

where, ‘h’ is the filter mask and $\mu_{I} = \mu_{x,i}$ as found from equation 6.9.

10. The hesitancy degree, which lies between 0 and 1 are given by,

$$\pi_I\left(g_{ij}\right)=(1-\mu_I\left(g_{ij}\right)\frac{\left|\mu_I\left(g_{ij}\right)-\mu_I^a\left(g_{ij}\right)\right|}{\max_{i=1}^{M}\left(\max_{j=1}^{N}\left(\left|\mu_I\left(g_{ij}\right)-\mu_I^a\left(g_{ij}\right)\right|\right)\right)}$$

(6.11)

and the non-membership degree at each pixel location is given by

$$\nu_I(g_{ij})=1-\mu_I(gi_{ij})-\pi_I(g_{ij}) \tag{6.12}$$

10. The A-IFS histon can be defined as ,

$$F_i(g)=\sum_{m=1}^{M}\sum_{n=1}^{N}\left(1+\mu\left(m,n\right)\right)\delta(I\left(m,n,i\right)-g)$$

(6.13)

‘g’ lies between 0 to L-1 (0 to 255) and i = { R , G, B}. ‘δ’ represents the impulse function.

$$\mu\left(m,n\right)=\exp\left(-0.5\left(\frac{d_T\left(m,n\right)}{\sigma}\right)^2\right) \tag{6.14}$$

σ - Standard deviation of the distance matrix

11.The total distance of all the pixels in a PXQ neighbourhood of size 3X3 is given by,

$$d_T(m,n) = \sum_{p \in P} \sum_{q \in Q} d\big(I(m,n)I(p,q)\big) \tag{6.15}$$

12. The Euclidean distance between two pixels, I(m,n) and I(p,q) is given by,

$$d\big(I(m,n),I(p,q)\big)=\left(\frac{1}{6}\sum_{i\in\{R,G,B\}}[(\mu^i\left(I(m,n)\right)-\mu^i\left(I(p,q)\right))^2+(\vartheta^i\left(I(m,n)\right)-\vartheta^i\left(I(p,q)\right))^2+(\pi^i\left(I(m,n)\right)-\pi^i\left(I(p,q)\right))^2]\right)^{0.5} \tag{6.16}$$

13. After calculating the Euclidean distance, a measure called roughness index is calculated, which is given by,

$$\rho = 1-\left(\left|f_i(g)\right| \div \left|F_i(g)\right|\right) \tag{6.17}$$

where '$f_i(g)$' is the histogram of the image. $F_i(g)$ represents a set of similar colour pixels of g^{th} intensity.

In the object region, roughness index is large and is close to unity. In boundary regions, this value is small and is close to zero. Thus, roughness index is useful in segregating the object regions from boundaries. Finally, region merging algorithm [71] is used to fine-tune the segmented output. After considering a number of images for analysis, the clusters with less than a threshold of 0.01 was found to be an apt value in order to be merged with the nearest clusters.

6.4 SIMULATION RESULTS

6.4.1 Qualitative comparison

Segmentation of images is carried out using A-IFS FCM approach and the output obtained is compared with that of the latest proposed A-IFS approach. The proposed technique is found to excel in performance, both qualitatively and quantitatively.

EXAMPLE 1

An example of a 'tree' image with background information shown in Figure 6.2 (a) is considered for segmentation using region based approach. Figure 6.2 (b) shows the output obtained using A-IFS method and Figure 6.2 (c) shows the output of the proposed A-IFS FCM technique.

Figure 6.2 (a) Tree image

Figure 6.2 (b) Segmented output in A-IFS technique

Figure 6.2 (c) Segmented output in A-IFS FCM technique

Figure 6.2 Segmented output of 'tree' image using A-IFS technique and A-IFS FCM technique

From the simulation results, it is inferred that the proposed approach gives a better segmented output. The reason is attributed to the methodology involved in the calculation of membership function in the proposed approach. The membership functions are calculated based on minimising the objective function. The iteration is stopped when the difference between the successive objective functions is less than 0.000001. Because of this very small difference, only a little error is involved in the calculation of membership values and hence segmentation output is superior.

The histogram plots of the 'red' component, 'green' component and 'blue' component of the 'tree' image are used in the calculation of roughness index and are shown in Figure 6.3, Figure 6.4 and Figure 6.5 respectively.

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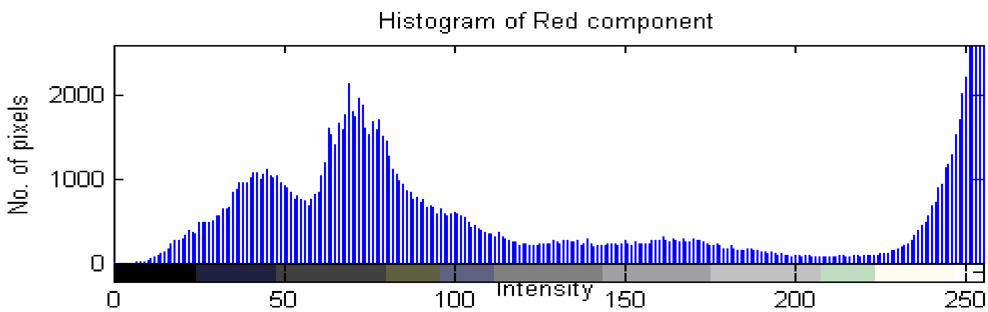
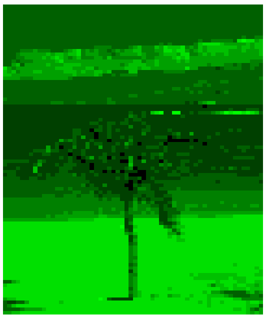


Figure 6.3 Histogram plot for 'red' component



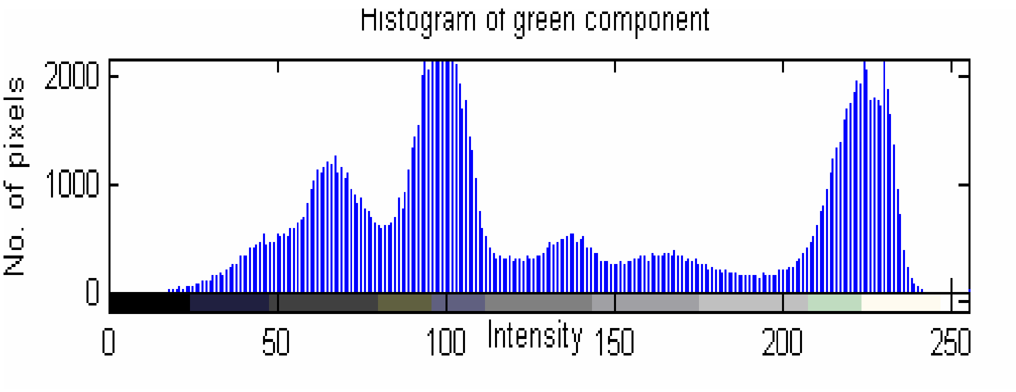


Figure 6.4 Histogram plot for 'green' component

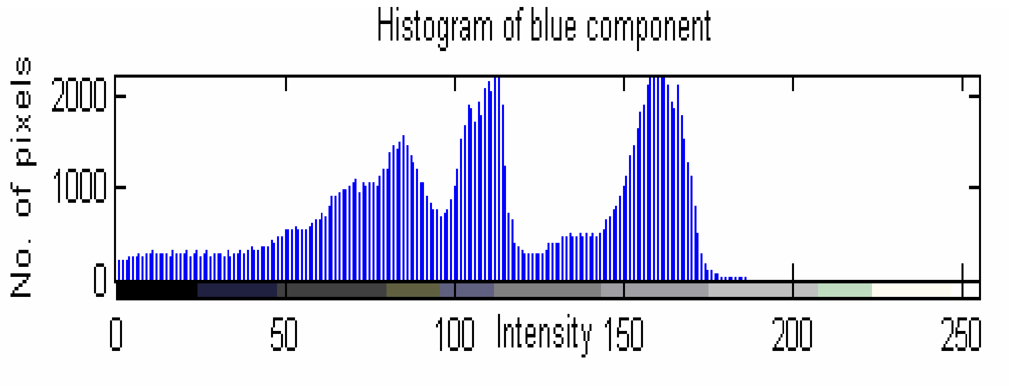


Figure 6.5 Histogram plot for 'blue' component

6.4.2 Roughness index plot

Roughness index is a ratio lying between 0 and 1. This value is large in the object region and small in the boundary.

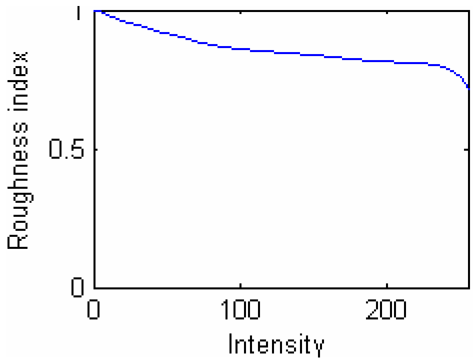


Figure 6.6 (a) Roughness index for 'red'component

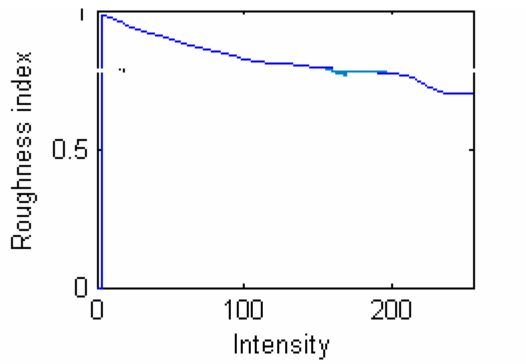


Figure 6.6 (b) Roughness index for 'green' component

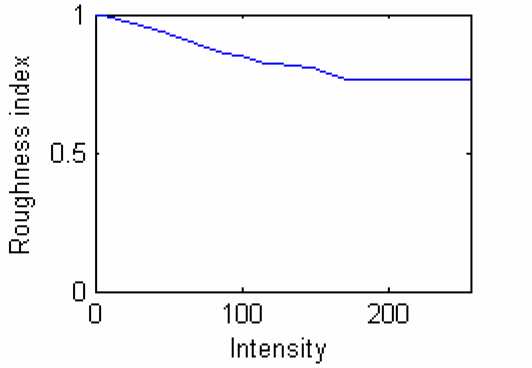


Figure 6.6(c) Roughness index for 'blue' component

Figure 6.6 Roughness index plots for the 'tree' image in A-IFS technique

There is only a slight droop in the roughness index plots of Figure 6.6(a), Figure 6.6(b) and Figure 6.6(c) and hence, the clear-cut demarcation between object region and the boundary could not be located precisely in A-IFS approach.

The roughness index plots for 'red' 'green' and 'blue' components in A-IFS FCM technique are shown in Figure 6.7(a) , Figure 6.7 (b) and Figure 6.7(c) respectively.

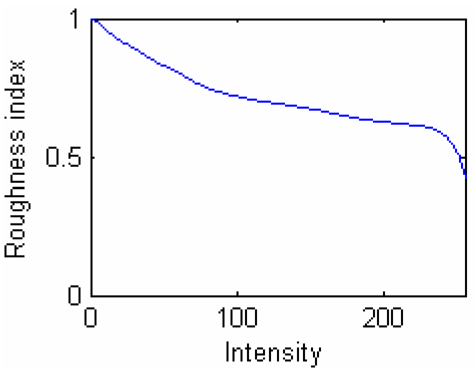


Figure 6.7 (a) Roughness index for 'red' component

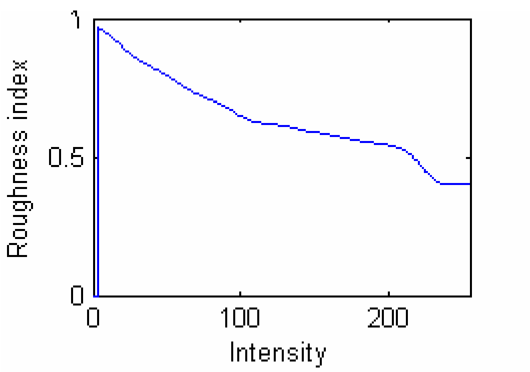


Figure 6.7(b) Roughness index for 'green' component

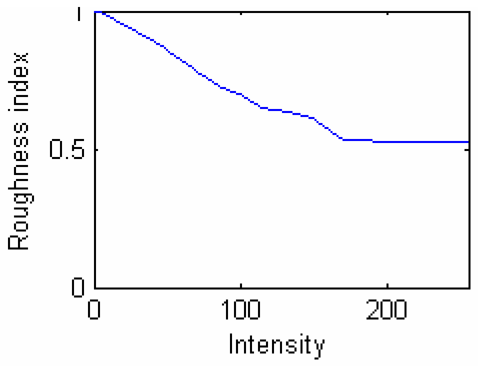


Figure 6.7 (c) Roughness index for 'blue' component

Figure 6.7 Roughness index plots for the 'tree' image in A-IFS FCM technique

In all the plots of Figure 6.7, the droop in the curves is found to be more compared to that of Figure 6.6. This clearly illustrates that the demarcation between object and boundary is well defined in this approach. Hence the segmentation output is found to be better compared to the A-IFS segmentation technique.

EXAMPLE 2

In this example, a fused image is considered for segmentation using A-IFS technique and A-IFS FCM technique. As it is clearly seen, the proposed approach yields a better segmented output due to the reasons already enumerated in the previous example.

Figure 6.8(a) Seashore

Figure 6.8(b) Segmented output in A-IFS technique

Figure 6.8 (c) Segmented outputs in A-IFS FCM technique

Figure 6.8 Segmented output of 'Seashore' image using A-IFS and A-IFS FCM techniques

6.4.3 Performance measures

PSNR is a common measure used for performance comparison of segmented images. It represents the region homogeneity of final partitioning. Higher the PSNR better is the segmented output. A comparison of the proposed approach with the A-IFS technique in terms of PSNR and RMSE values are illustrated in Figure 6.9 and Figure 6.10 respectively.

6.4.3.1 PSNR comparison

PSNR comparison of A-IFS technique and A-IFS FCM technique depicted in Figure 6.9 proves the superiority of the proposed technique.

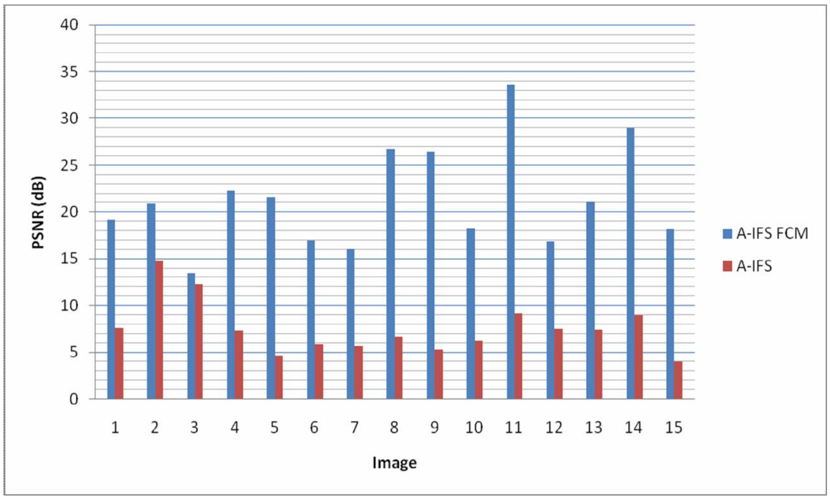


Figure 6.9 PSNR comparison of A-IFS technique and A-IFS FCM technique

6.4.3.2 RMSE comparison

A comparison in RMSE values confirms that A-IFS FCM approach excels better than that of the A-IFS approach to segmentation.

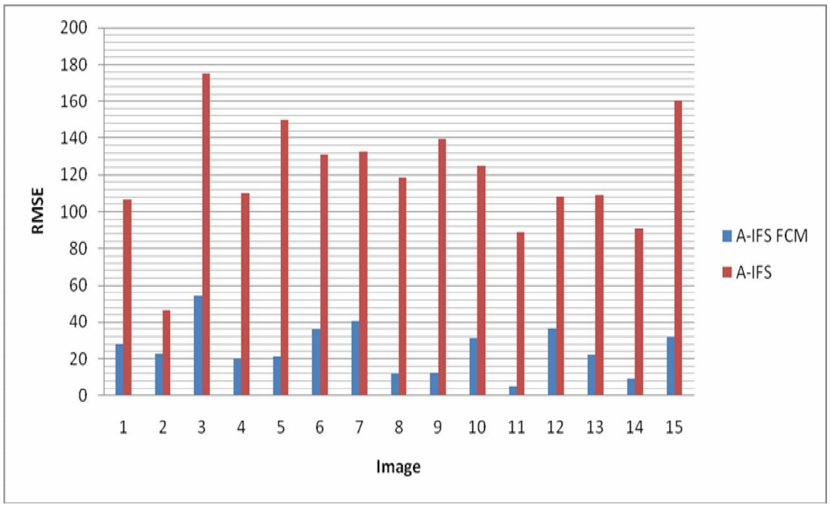


Figure 6.10 RMSE comparison of A-IFS technique and A-IFS FCM technique

6.5 CONCLUSION

This work integrates FCM algorithm and A-IFS algorithm into a novel approach to perform image segmentation. The performance comparison is analysed both qualitatively and quantitatively. The simulation results prove the superiority of the proposed approach, which can be judged visually from the output images and also from the quantitative comparisons made.

CHAPTER 7

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The conclusions drawn on the research contributions based on simulation results is presented in this chapter. A few problems in the focussed area are also explored for future research perspective.

7.1 CONCLUSIONS

The transform domain approach using DTCWPT is attempted in the research work for monochrome and IR image fusion. The reason for using DTCWPT is also justified and an attempt had been made to improve the performance of fusion. Both, pixel based and region based approaches to image fusion using DTCWPT are considered. The simulation results obtained are analysed and compared with that of the pixel based and region based fusion using DTCWT. The results obtained indicate the superior performance of the work compared to the latest existing DTCWT based fusion technique. Further, performance comparisons carried out in terms of PSNR, RMSE and entropy substantiate the excelling performance of the proposed technique.

Since, it is difficult to distinguish between small and gradual variations in gray values in a monochrome image, the notion of extending the use of DTCWPT for colour image fusion is also proposed. Fusion of colour and IR images were carried out using DTCWPT in both pixel based and region based approaches. Since, fusion of colour image with an IR image cannot be carried out directly, the colour image is first split into intensity, hue and saturation components. Next, the intensity components of colour image are fused with the intensity components of IR image, in the transform domain. After fusion, inverse transformation is done to get the fused output in spatial domain. Then, hue and saturation components are added to get the fused colour output. Finally, the HSI colour output is once again converted to RGB format. Different fusion strategies were adopted for pixel based and region based techniques. Maximum selection rule is the fusion strategy considered for pixel based fusion. Owing to the drawbacks of this technique, region based fusion was attempted, in which segmentation plays a vital role prior to fusion. Since, effective fusion depends on an efficient segmentation, due attention was given to achieve this goal in region based fusion. Colour image fusion based on region features produced visually appealing results, when compared with pixel based output. Further, the fused output could successfully preserve the salient information content present in the two input images. To substantiate the results obtained qualitatively, performance comparisons were carried out on the basis of UIQI and entropy. Both qualitative and quantitative comparisons ensure better performance of region based colour image fusion using DTCWPT.

Further work was focussed on embedding the watermark in the DTCWPT coefficients of the fused CT and MR medical image for authentication purpose in telemedicine applications. Information pertaining to the details of patients is considered as a logo to be embedded in the image. Watermark has been made invisible, so that tampering becomes a tricky job. Further, there are more number of subbands in DTCWPT compared to DTCWT, because of which tampering becomes a difficult task. Addition of noise during teletransfer is considered to a small extent, followed by filtering operation to counteract this problem. Watermark extraction and recovery of image could be achieved successfully, which could be evidenced from the visual results obtained. Further, performance comparisons carried out between DTCWPT and DTCWT watermarking approaches in terms of normalised cross correlation, PSNR and MSE validate the superiority of the proposed technique. But, the penalty to be endured is that, DTCWPT involves more number of subbands compared to DTCWT, because of which computational complexity is increased.

Final phase of the work was focussed on segmentation the fused image, which is of paramount importance in many imaging applications. A novel technique clubbing FCM clustering and the advanced A-IFS approach was utilised to carry out segmentation of fused image and was proved to be successful. From the visual output and from the analysis based on PSNR and RMSE, this technique seems to be fruitful in producing better results.

7.2 FUTURE RESEARCH DIRECTIONS

The following suggestions are presented for further investigations. To improve the shift invariance property of DTCWPT, fractional directional Hilbert transform could be considered instead of using Hilbert transform. Another possibility for future work is the fusion of multiple images. Effective fusion of 3-D images is yet another challenging problem. Increasing the number of decomposition levels would result in better performance, but at the cost of increased complexity. The extension of this analysis could also be attempted in real time applications.

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