Chapter 4

Image Pre-processing and Fusion for Change Detection

4.1 INTRODUCTION

Image fusion is the process of merging two or more images to produce single composite image to reveal more inclusive information for further analysis. Over the last decade, image fusion has found enormous applications in the area of remote sensing. Varieties of remote sensing methods such as aerial photography, multispectral, active and passive microwave exist and are continuously producing different types of images including multi-temporal images, multispectral images, hyperspectral images and multiresolution images. Real world remote sensing applications not only require images with high spatial resolution, but also images with sufficient spectral resolution for accomplishment of change detection. It is difficult to obtain the image of high-spatial resolution and high-spectral resolution at the same time and mostly it is limited by the spatial and spectral resolution of the imaging system. Hence, an appropriate pre-processing and enhancement process is required to improve the quality of the images that are continued to be analysed. Initially, to use remote sensed images for change detection the images are subjected to radiometric, geometric correction followed by enhancement through noise reduction. The resultant of applying these tasks provides a single form of data from different sets and hence leads to the easy image registration process. In addition, to detect changes effectively, it is required to have both high spatial and high spectral details in a single image and hence the process of image fusion is attempted. An elaboration of the established process for multi-temporal multispectral Landsat image is delineated in the subsequent sections.

4.2 IMAGE PRE-PROCESSING

Usually, the pre-processing of remote sensed images is carried out to eliminate data registration errors thereby correcting distorted or degraded data to create a trustworthy representation of the original images. It involves the initial processing of raw image
data to correct for the radiometric corrections, geometric corrections and noise removal. The radiometric corrections are performed to remove sensor noises that induce changes in scene illumination. The geometric corrections are carried out to avoid the geometric distortions. It is accomplished by establishing a relationship across image coordinate system and geographic coordinate system. An association is created between calibration data of sensor, measured data of position, ground control points and atmospheric conditions and hence the geometrical distortions are suppressed. Thus, these pre-processing mechanisms help to create firm base of source image which can be subjected to further processing.

4.3 IMAGE ENHANCEMENT

In general, image enhancements in remote sensed image include the application of several tasks to correct the acquired images suitable for processing and analysis. It is the process that makes the image better suitable for interpretation. In the case of remote sensed images, this process helps in improving the quality of information present in the images using point operations, local operations and global operations. The point operations change the value of pixel independent of other pixels. The information enhancement of the images can also be achieved through image reduction, image magnification, transect extraction, contrast adjustments (linear and non-linear), band rationing, spatial filtering, Fourier transformations, principle components analysis, texture transformations, and image sharpening. The local operations change the value of individual pixels in the context of the values of neighboring pixels by means of filtering while global operations expects all digital numbers (DN – generic term for pixels) to have effect on DN.

Though the scope of preprocessing techniques are wider, there is a challenge exists in the selection of appropriate preprocessing techniques suitable for the chosen application. Moreover, in most of the cases, the availability of raw images is a major concern and hence, researchers prefer to use the images from the standard library. The images that are present in the standard library are already preprocessed one and hence, it requires only few simple processes to be carried out in the name of preprocessing.

In view of change detection application, mostly, preprocessed and enhanced images are taken as the test images from the library and hence, the regular process
commences from the creation of difference images which are very much useful for the subsequent fusion process.

4.4. DIFFERENCE IMAGE CREATION

Creation of difference image is a usual process attempted to highlight the difference between two considered acquisitions in image processing applications. Several unique operations are traditionally followed for creating difference image and are tabulated in Table 4.1.

Table 4.1: Comparison of Difference Image Creation Methods

<table>
<thead>
<tr>
<th>Difference Image Creation Methods</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image Differencing (Coppin and Bauer, 1996)</td>
<td>➢ Simple ➢ Easy to interpret output</td>
<td>➢ No complete matrix of change information ➢ Optimal selection of threshold ➢ Change information in binary form</td>
</tr>
<tr>
<td>Image regression (Coppin et al., 2004)</td>
<td>➢ Reduces the adverse effects by atmospheric conditions and sun angles</td>
<td>➢ Accurate regression function needed to compute difference ➢ Poor for detecting subtle changes</td>
</tr>
<tr>
<td>Image rationing (Rignot and van, 1993)</td>
<td>➢ Effective in handling calibration errors</td>
<td>➢ No complete matrix of change information ➢ Abnormal distribution of results</td>
</tr>
<tr>
<td>Vegetation Index differencing (Nodberg and Everston, 2005)</td>
<td>➢ Reduces impacts of topographical effects and illumination</td>
<td>➢ Random or coherence noise ➢ Change information in binary form</td>
</tr>
<tr>
<td>Change Vector Analysis (Bovolo)</td>
<td>➢ Process any number of spectral bands desired ➢ Produces detailed changed information</td>
<td>➢ Difficult to identify land cover change trajectories ➢ Strictly require</td>
</tr>
</tbody>
</table>
Based on the simplicity and benefit of addressing all spectral conditions, two methods such as ADM and CVA are identified for the difference image creation. In order to demonstrate the effect of the identified methods, two multispectral images acquired by the Landsat Thematic Mapper Sensor of the Landsat-5 satellite and Landsat Operational Land Imager Sensor of the Landsat-8 satellite in an area of Huelva, Spain on October 12, 1984 and August 12, 2014 is used. The band combinations used to create the multispectral images are 3, 2, 1 (R-G-B) and 4, 3, 2 (R-G-B) visible color which are downloaded from (https://earth.esa.int/web/earth-watching/change-detection/content/-/article/huelva).

4.4.1 ABSOLUTE DIFFERENCE METHOD (ADM)

The absolute difference method of creating difference image is a task which is carried out to find the difference between the corresponding pixels of given images $I_A$, $I_B$. The ultimate purpose of the task is to subtract background variations from a scene so that the foreground objects may be more easily analyzed.

The task is initiated by subtracting the pixel reflectance spectra of the Landsat image acquired at time T1 and T2. The difference image is obtained using absolute differencing which is shown here,

$$I_{AD} = |\sum_{i}^{N} I_{Ai} - I_{Bi}|, \text{ for } i = 1,2,...N$$

where, N is the number of bands,

$I_A$ is the multispectral image at time T1,

$I_B$ is the multispectral image at time T2.

A simple illustration of task is explained through Fig. 4.1. where the pixel values of $I_A$ and $I_B$ are randomly taken.
Fig. 4.1: Absolute Differencing Method

Generally, the higher intensity pixels are considered as changed area and the lower intensity pixels are considered as unchanged area. The threshold value set here is based on the pixel intensity variations of the reference map. According to the absolute differencing method shown in Fig. 4.1 if the threshold is taken as 40, then the values obtained in R1C4, R1C5, R2C3, R2C4, R2C5, R3C3, R4C5 and R5C5 where R represents Row and C represents Column seems to have changes compared to other locations.

4.4.2 CHANGE VECTOR ANALYSIS (CVA)

Change Vector analysis is a method that allows simultaneous analysis of multiple images for change detection. It uses two spectral channels to map the magnitude and the direction of change between the two spectral input images. The illustration of the same is given in Fig. 4.2.
The difference image using CVA is determined by subtracting the spectral change vectors of the images acquired at different timings T1 and T2. Let $I_{CVA} = \{D_{pq}, \ 1 \leq p \leq m, \ 1 \leq q \leq n\}$ be the difference image obtained using CVA technique is as follows,

$$D_{pq} = \sqrt{\frac{\sum_{i=1}^{N}(D_{pq}^i(I_A) - D_{pq}^i(I_B))^2}{N}}, \quad (4.2)$$

where $D_{pq}(I_A)$ and $D_{pq}(I_B)$ are gray levels at the position $(p, q)$ in the $i^{th}$ band of the images $I_A$ and $I_B$.

Thus difference image with respect to images taken at different timings is created. The difference images generated are further subjected to image fusion process to explore the possible changes.

### 4.5 ANALYSIS OF VARIOUS FUSION METHODS

In general, Image fusion involves merging of two or more images in such a way to retain the most desirable characteristics of each image (Amolins et al., 2007). It aims towards the integration of disparate and complementary data to enhance the information apparent in the images as well as to increase the reliability of the interpretation (Pohl and Van, 1998). In order to detect changes in remote sensing multispectral images, two different approaches are usually followed, one is with image fusion and the other is without image fusion. Change detection without fusion results in loss of spatial and spectral information and leads to false positive results on
the other hand, change detection with fusion leads to provide more data for better interpretation. Considering the advantages of image fusion in change detection, the difference image obtained is fused to extract the inherent details for detecting changes.

Prior to the design of fusion method, the usefulness of different fusion techniques had been studied. According to the literature, Multiplication (MLT) algorithm, Modified Brovey (MB) algorithm, High-Pass Filter (HPF) algorithm, the Smoothing Filter-based Intensity Modulation (SFIM) algorithm, the Principal Components Analysis (PCA), the Intensity-Hue-Saturation (IHS), Discrete wavelet transform (DWT) are considered to be effective methods for image fusion. All of the above-mentioned methods can realize the fusion of multispectral and high-resolution images. Ultimately, these methods help in improving the spatial resolution and preserve the spectral information to certain degree.

To demonstrate the effectiveness of the fusion process, initially, the suitability of these methods is investigated by applying fusion on multispectral images. An attempt is made to understand the effectiveness of fusion process in multispectral images using PCA, DWT, SWT, Ehlers and Sparse Representation (SR).

4.5.1 IMAGE FUSION USING PCA

In general, PCA is a generic method for transforming the input data into a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate called the first principal component (Naidu et al., 2008). For the process to be carried out, multispectral remote sensing images taken at two different timings are considered as input. The fusion is achieved by weighted average of images to be fused. The weights for each source image are obtained from the eigenvector corresponding to the largest eigenvalue of the covariance matrices of each source. The adopted methodology is illustrated in Fig. 4.3.
Legend: PCA – Principal Component Analysis,

Fig. 4.3: Image fusion using PCA

As the variance of multispectral images obtained from eigen vector are heterogeneous, standardization is brought between the components of the source images to be fused. Hence, the fused image is computed using the equation

\[ \text{Fused Image} = P1*I_A + P2*I_B \]  \hspace{1cm} (4.3)

Where, P1- normalized component of multispectral image 1
P2- normalized component of multispectral image 2
I_A- multispectral image 1
I_B- multispectral image 2

The procedure adopted for the same is given below,

**Input: Multispectral images I_A and I_B**

**Output: Fused Image F**

**Begin**

*Organize the data into column vectors of array X*

*Compute empirical mean \( \mu_e \) of column*

\[ \mu_e = \frac{1}{M} \sum_{k=1}^{M} X_k \]

*Subtract \( \mu_e \) from each column vector*

*Compute covariance matrix \( C_x \)*

\[ C_x = [X_kX_k^T] \]

*Compute eigenvectors \( E_v \) and eigenvalues \( \lambda_i \) of \( C_x \)*

*Arrange Eigen value in descending order*

*Extract the first column of \( E_v \) to compute P1 and P2 as,*

\[ P1 = \frac{E_v(1)}{\sum{E_v}} \quad \text{and} \quad P2 = \frac{E_v(2)}{\sum{E_v}} \]

*Fused Image is computed as,*

\[ F = P1I_A + P2I_B \]

**End**
4.5.2 IMAGE FUSION USING DWT

Generally, wavelet-based analysis of signals is an exciting and relatively recent tool applied for image fusion. Similar to Fourier series analysis, wavelet transformation is also based on a decomposition of a signal using an orthonormal family of basic functions (Naidu et al., 2008). A wavelet has its energy concentrated in time and is suited for analysing the transient and time-varying signals.

To generate a fusion decision map, firstly a wavelet transform is performed on each multispectral image using a set of fusion rules. The fused wavelet coefficient map is constructed using fusion decision map from the wavelet coefficients of the multispectral images. Finally, by performing the inverse wavelet transform, the fused image is created.

The single level fusion and multilevel fusion process using DWT is depicted in Fig. 4.4 and Fig. 4.5.

Fig. 4.4: Image Fusion using Single Level DWT

Fig. 4.5: Image Fusion using Multilevel DWT
The steps involved in the image fusion using DWT are presented below.

**Input:** Multispectral images $I_A$ and $I_B$

**Output:** Fused Image $F$

**Begin**

- Apply wavelet transform on the input images through Daubechies wavelet,
  \[
  W_\phi (j, x, y) = \frac{1}{\sqrt{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} M1(x, y)\phi_{j,m,n} (x, y)
  \]

- Extract the approximations and coefficients for both source images
- Extract the four bands ( HHa, HLa, LHa, LLa) of the multispectral image $I_A$.
- Extract bands (HHb, HLb, LHb, LLb) of the multispectral image $I_B$.
- Merge the coefficients by choosing maximum fusion rule
- Apply Inverse wavelet transform on the merged coefficients to obtain the fused image $F$.

**End**

### 4.5.3 IMAGE FUSION USING SWT (MULTILEVEL TRANSLATION INARIANT WAVELET TRANSFORM)

The Discrete Wavelet Transform is not a time invariant transform where DWT of a translated version of a signal ‘$x$’ is not the same as the DWT of the original signal. This property of DWT will not be suitable for performing change detection. Hence, Translation invariant wavelet transformation (SWT) is designed to overcome the lack of translation invariance in discrete wavelet transformation (Beaulieu et al., 2003). Translation-invariance is achieved by eradicating the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of $2^{i-1}$ in the $i^{th}$ level of the process. Therefore in the attempted methodology, the SWT is applied as a high and low pass filter in each level of data. The 2D SWT is totally based on the idea of non-decimation where for each level zeros are padded for modifying filters. This process totally eludes the effect of down sampling in the forward transform while up sampling is evaded in the inverse transform.

The flow diagram for the translation invariant wavelet transform is given in Fig. 4.6.
The procedure adopted for fusion using SWT is enlisted below:

*Input:* Multispectral images $I_A$ and $I_B$

*Output:* Fused Image $F$

*Begin*

- Decompose the image using SWT
- Extract two sub bands, LFC and HFC.
  
  One has three detail sub bands and the other has approximation result.
- Compute the average of the approximation parts.
- Subtract horizontal approximation values
- Multiply absolute values with the horizontal details to obtain fused image.
- Subtract vertical approximation values
- Multiply absolute values with the vertical details to obtain fused image.
- Apply inverse SWT to obtain the fused image.

*End*

4.5.4 IMAGE FUSION USING EHLERS METHOD

The Ehlers fusion technique was developed as a fusion method that would better preserve the spectral characteristics of the multispectral data set while improving the spatial quality of the fused image (Ehlers, 2004). The driving principle behind
preserving the spectral characteristics is to spatially enhance the multispectral image, in terms of high frequency changes such as edges and high frequency grey level changes in an image without adding new grey level information to its spectral components particularly, in areas of homogenous land cover features. According to the method, first three low resolution multispectral band images are transformed to Intensity Hue Saturation (HIS) image. Later, a two dimensional Fast Fourier Transformation (FFT) is used to transform the intensity (I) component of the source image and a high resolution image into the frequency domain. A low pass filter and an inverse high pass filter are applied to the intensity spectrum, and the spectrum of high resolution image respectively. Subsequently, an inverse FFT is performed on these filtered images, to form a fused intensity image component which is expected to be composed of with high and low frequency information. The image information can be extracted from high and low resolution images respectively. This algorithm was developed specifically for a spectral characteristics preserving image fusion.

The flow diagram for the Ehlers fusion is given in Fig. 4.7.

![Flow Diagram](image)

Legend: MHP- Multispectral High pass filter,
ILP- Intensity Low pass filter,
FFT- Fast Fourier transforms,
HIS- Intensity, Hue and Saturation.

Fig. 4.7: Image Fusion using Ehlers Method

The procedure adopted for Ehlers fusion is given below,

*Input: Multispectral images $I_A$ and $I_B$

*Output: Fused image $F$

*Begin*

*Apply Fourier transform to the multispectral image $I_A$.**
Apply high pass filter to $I_A$.

Convert multispectral image $I_B$ to HIS form (Intensity image).

Apply Fourier transform to the intensity component of intensity image.

Apply low pass filter to the intensity image.

Apply inverse Fourier transform and fuse the intensity image with the high pass filtered image ($I_A$).

Apply inverse HIS transform to obtain the fused RGB image.

End

4.5.5 IMAGE FUSION USING SPARSE REPRESENTATION

Sparse representation is another widely used method to represent an image. This kind of representation normally reduces the memory space that is occupied by an image. In case of remote sensed image this type of representation would support in high dimensional space which is very much needed for faster image processing. In usual block oriented transforms like DCT, the sparseness can be introduced through thresholding of the transform or using wavelet transform and hence the image is approximated as linear combinations of few atoms to form dictionary (Liu et al., 2014). It is the process of computing the representation coefficients, ‘x’, based on the given signal ‘y’ and the dictionary D. Therefore the training dictionary is said to have number of overlapped patches mined from observed images.

The outcome learned from these training patches of the dictionary produces better results. Image signals $x \in \mathbb{R}^n$ can be estimated as,

$$x = D \alpha$$

where, $D \in \mathbb{R}^n$ is the dictionary,

$\alpha$ is the sparse vector.

To sparse vector containing smallest number of non-zero elements is obtained using equation 4.5.

$$\min \| \alpha \|_0 \quad \text{such that} \quad \| x - D \alpha \|_2^2 \leq q \quad (4.5)$$

where $\| \alpha \|_0$ denotes the number of non-zero components in $\alpha$ and $q$ is the approximated error of the input image. The OMP (Tropp and Anna, 2007) method is used for extracting the sparse coefficients.

The illustration of the process is shown in Fig. 4.8.
The procedure adapted for sparse representation is given below,

**Input:** Multispectral images $I_A$ and $I_B$

$I_A = $ Multispectral image 1

$I_B = $ Multispectral image 2

**Output:** Fused image $F$

**Initialize:** $q = 0.1$, block size $= 8 \times 8$

**Begin**

Represent the images using,

$$\min \| \alpha \|_0 \text{ such that } \| x - D \alpha \|_2^2 \leq q$$

Extract the patches based on OMP

Update the dictionary

Fuse sparse coefficients $\hat{V}_f$

Restore fused image vectors as,

$$\hat{V}_1 = DS_1, \hat{V}_2 = DS_2, ..., \hat{V}_k = DS_k$$

Reconstruct fused image vector,

$$\hat{V}_f = DS$$

**End**

Finally the fused image is reconstructed from $\hat{V}_f$

**4.6 COMPARISON OF FUSION METHODS**

The suitable fusion method for detecting changes in multispectral multi-temporal Landsat images is arrived as a consequence of investigation made with respect to popular fusion techniques such as PCA, DWT, SWT, Ehlers and SR. Each of these
methods has its own limitation towards determining the changes in remote sensed images. The limitations of these methods understood at the end of the study on multi-temporal image fusion are highlighted in the Table 4.2.

Table 4.2: Comparison of Image Fusion Techniques

<table>
<thead>
<tr>
<th>Image Fusion Techniques</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>➢ Only the first eigenvector is used to describe the data set.</td>
</tr>
<tr>
<td></td>
<td>➢ Produces spectral degradation.</td>
</tr>
<tr>
<td>DWT</td>
<td>➢ Omits down sampling and up sampling in both forward and reverse transformation respectively due to which partial fusion of details alone expected.</td>
</tr>
<tr>
<td></td>
<td>➢ The spectral content of small objects is lost.</td>
</tr>
<tr>
<td>SWT</td>
<td>➢ Requires more space to store each level of transformation details.</td>
</tr>
<tr>
<td></td>
<td>➢ Feature based fusion is addressed inadequately.</td>
</tr>
<tr>
<td>Ehlers</td>
<td>➢ Preserves the colour content but reduces the spatial information</td>
</tr>
<tr>
<td>Sparse Coding</td>
<td>➢ Minimized level of correlation across multispectral channels.</td>
</tr>
<tr>
<td></td>
<td>➢ Spatial information of source images is less considered.</td>
</tr>
</tbody>
</table>

Though the SR method showed acceptable outcome, yet it can be improved to yield better fusion data that would improve the further process. Therefore, enhancement on to sparse coding is proposed.
4.7 THE DEVELOPED IMAGE FUSION PROCESS USING THE PROPOSED ENHANCED SPARSE CODING

The proposed enhanced dictionary based sparse representation (EDSR) is applied on the multi-temporal multispectral Landsat images. The process for the same is illustrated in the Fig. 4.9.

Two Landsat images acquired at different timings T1 and T2 are considered for analysis of multi-temporal image fusion. Images acquired from satellite might have some noise due to the external disturbances that might happen during acquisition process. Before the images are processed, the unwanted noise that is expected to affect the outcome is removed using Gaussian low pass filter. The filter removes the high contrast pixels that would not contribute for any interpretation. The pre-processed images are then subjected to fusion using the enhanced dictionary based sparse representation.

The training image patches are extracted from pre-processed multi-temporal multispectral Landsat images using an operator $R$. Extracting image patch $x$ from observed image $X$ can be represented as,

$$x_j = R_j(X) \quad (4.6)$$
where $R_j(.)$ is an operator that extracts the patch $x_j$ from location (j) in the image $X$. Followed by the patch extraction, image reconstruction is carried out through transpose $R^T_j(.)$. Since, too small image patches loose compactness of the dictionary and too large patches affects the multispectral features of the image, the size of image patches is selected to be $\sqrt{64} \times \sqrt{64}$. Each extracted patch is localized by subtracting each pixel of the patch from its mean and subsequently converting into a column vector as the process produce vectors $v_1$ up to $v_j$ where $j$ is the index of last vector. Finally, the generated patched from an image $X$ are combined to represent a matrix $V$ and the process is repeated for both the source images. Matrix $V$ is further subjected to sparse coding to locate the basis vector. Usually to determine the best basis vector out of sparse coding lower bound of an error signal is used as a deciding parameter. Considering this fact an enhanced sparse coding is suggested where this deciding parameter is determined by,

$$\min \|X - DS\|_2^2 \leq q \text{ such that } p \leq \|S\|_2 \leq q \quad (4.7)$$

where, $p$ is the lower bound of the sparse regularization term. Henceforth, the dictionary is initialized with extracted image patches subsequently patches are sparse coded and updated in the dictionary. The OMP (Tropp and Anna, 2007) method to compute sparse coefficients for each image is as given below,

$$S = \min_{s \in \mathbb{R}^m} \frac{1}{2} \|X - DS\|_2^2 \text{ such that } \|S\|_0 \leq q \quad (4.8)$$

\begin{verbatim}
Begin
Initialization: $S = 0$, residual $r = X$, active set $\Omega = \emptyset$

For each of the source image,

While $\|S\|_0 < q$

Begin

Repeat

Select the element with maximum correlation with the residual

$$\hat{i} = \arg \max_{i=1,2,\ldots,m} |d_i^Tr|$$

Update the active set, coefficients and residual

$$\Omega = \Omega \cup \hat{i}$$

$$S_\Omega = (d_\Omega^Td_\Omega)^{-1}d_\Omega^Tr$$

$$r = X - d_\Omega S_\Omega$$

Until

End

End
\end{verbatim}
Therefore the sparse coefficients \( S_{1\Omega} \) and \( S_{2\Omega} \) are obtained through the designed procedure for the pre-processed images. The coefficients \( S_{1\Omega} \) and \( S_{2\Omega} \) are fused together by using maximum absolute rule to yield fused sparse coefficients \( S_{F\Omega} \). Subsequently, the fused vector \( W_F \) is computed using the training dictionary fused sparse coefficients as,

\[
W_F = DS_{F\Omega}
\]  

(4.9)

The fused vectors \( W_F \) is reshaped into a block of 8 x 8 and are adjoined to form the fused image using the EDSR procedure which is stated as,

**Input:** LANDSAT images \( I_A \) and \( I_B \) at time \( T1 \) (1984) and \( T2 \) (2014)

**Output:** Fused image \( F \)

**Initialize:** Set overlap = 5, dictionary size = 64x256, \( q = \sqrt{2 \log(size(D, 2))} \)

\( \text{patch size} = \sqrt{64} \times \sqrt{64} \)

**Begin**

Perform Gaussian low pass filter to both LANDSAT images at time \( T1 \) and \( T2 \).  
Use image \( I_A \) to determine 2-dimension grids of the images.  
Extract image patches from each source images \( I_A \) and \( I_B \).  
Construct dictionary using Improved Sparse Coding (ISC) as follows,

\[
D = \min_D \| X - DS \|_2^2 + \lambda \| S \|_1
\]

such that \( p \leq \| S_i \|_2^2 \leq q \), \( i = 1, ..., K \)

Use Orthogonal Matching Pursuit (OMP) method to compute sparse coefficients for each image,

\[
S = \min \| S \|_0 \text{ such that } \| X - DS \|_2^2 \leq q
\]

Select only maximum absolute of the fused vectors,

\[
S^k_F = S^k_{I_A} \text{ if } \left( \| S^k_{I_A} \|_1 \gtrsim \| S^k_{I_B} \|_1 \right) \text{ otherwise, } S^k_F = S^k_{I_B}
\]

Reconstruct fused image as,

\[
F = D^T S = \sum_{k=1}^{n} R^T_k(DS_k)C / \sum_{k=1}^{n} R^T_k(1s)
\]

**End**

According to EDSR procedure, an adaptive regularization parameter ‘q’ is calculated based on the size of the dictionary. An improved sparse coding (ISC) is used for constructing the dictionary and the sparse coefficients of images are
computed through OMP. In order to fuse the image, the maximum absolute fused vectors are chosen. Subsequently, the fused image reconstruction is carried out.

The EDSR takes advantage of the adaptive regularization parameter and selection of maximum absolute fused vectors for fusion.

A comparative study of the existing and the proposed method is carried out to highlight the effectiveness of the proposed method over the existing method. The evaluation is performed with respective to the metrics Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross Correlation (NCC), Structural Content (SC), Normalized Absolute Error (NAE) (Naidu et al., 2008; Sumathi and Barani, 2012; Jagalingam and Hegde, 2015), Mutual Information (MI) (Haghighat et al., 2011) and Feature Mutual Information (FMI) (Haghighat and Masoud 2014). The definitions of these metrics are provided in the following subsection.

4.8 QUALITY METRICS AND DEFINITION

In order to verify the results obtained through the identified process, simple image metrics were considered to measure the various features of the fused image to get a better depiction of quality measure.

**Root Mean Square Error**

The root mean square error (RMSE) is the simplest, and the most widely used, full-reference image quality measurement. The RMSE is calculated based on the equation given by

\[
RMSE = \sqrt{\frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (I_{ij} - F_{ij})^2}
\]  
(4.10)

where, \(I_{ij}\) is the multispectral image, \(F\) is the fused image to be assessed, \(i\) is the pixel row index, \(j\) is the pixel column index and ‘\(m \times n\)’ is the size of the image.

**Peak Signal to noise ratio**

PSNR computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and fused image. The higher the PSNR, the better is the quality of the fused image.
\[ PSNR = 10 \times \log_{10} \frac{\text{peak}^2}{\text{MSE}} \quad (4.11) \]

where, \( \text{peak}^2 \) is the maximum possible pixel value of the image. MSE is the mean square error of the image.

**Normalized Cross Correlation**

The closeness between two digital images can also be quantified in terms of correlation function. Normalized Cross-Correlation (NCC) measures the similarity between two images and is given by the equation,

\[ \text{NCC} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} I_{Bij} \times F_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} (I_{Bij})^2} \quad (4.12) \]

where, \( I_B \) is the multispectral image, \( F \) is the fused image to be assessed, \( i \) is the pixel row index, \( j \) is the pixel column index and ‘m x n’ is the size of the image.

**Structural Content**

Structural Content (SC) is also called as correlation based measure and it measures the similarity between two images. SC is given by the equation,

\[ \text{SC} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (I_{Bij})^2}{\sum_{i=1}^{m} \sum_{j=1}^{n} (F_{ij})^2} \quad (4.13) \]

where, \( I_B \) is the multispectral image, \( F \) is the fused image to be assessed, \( i \) is the pixel row index, \( j \) is the pixel column index and ‘m x n’ is the size of the image.

**Normalized Absolute Error**

NAE is average of absolute difference between the reference image and test image. It is given by the equation,

\[ \text{NAE} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} |I_{Bij} - F_{ij}|}{\sum_{i=1}^{m} \sum_{j=1}^{n} I_{Bij}} \quad (4.14) \]

where, \( I_B \) is the multispectral image, \( F \) is the fused image to be assessed, \( i \) is the pixel row index, \( j \) is the pixel column index and ‘m x n’ is the size of the image.

**Mutual Information**

Mutual information is an image fusion metric which calculates the amount of information conducted from the source images to the fused image. Considering two
source images $I_A$ and $I_B$, and the fused image $F$, the amount of information that $F$ contains about $I_A$ and $I_B$ is calculated as:

$$I_{FA}(f; a) = \sum_{f,a} P_{FA} (f, a) \log_2 \frac{P_{FA}(f,a)}{P_F(f)P_A(a)}$$

$$I_{FB}(f; b) = \sum_{f,b} P_{FB} (f, b) \log_2 \frac{P_{FB}(f,b)}{P_F(f)P_B(b)}$$

where $P_{FA}(f, a)$ and $P_{FB}(f, b)$ are the joint probability distributive function between $F$ and $I_A$, $I_B$. $P_F(f)$, $P_A(a)$ are the marginal distributive functions of $F$ and $I_A$ and $P_F(f)$, $P_B(b)$ are the marginal distributive functions of $F$ and $I_B$ respectively.

Consequently, the image fusion performance measure can be defined as:

$$MI_F^{AB} = I_{FA}(f; a) + I_{FB}(f; b)$$

(4.17)

**Feature Mutual Information**

Feature Mutual information (FMI) is a non-reference image fusion metric based on mutual information of image features depending on the original images and fused image. The amount of feature information, which $F$ contains about $I_A$ and $I_B$, is individually measured with respect to MI as:

$$I_{FA} = \sum_{f,a} P_{FA} (f, a, z, w) \log_2 \frac{P_{FA}(f,a,z,w)}{P_F(f)P_A(a)P_A(z)P_A(w)}$$

$$I_{FB} = \sum_{f,b} P_{FB} (f, b, z, w) \log_2 \frac{P_{FB}(f,b,z,w)}{P_F(f)P_B(b)P_B(z)P_B(w)}$$

(4.18)

(4.19)

where, $z$ is the feature used and $w$ is the sliding window of size 3.

Eventually, the FMI metric is:

$$FMIA^{AB} = I_{FA} + I_{FB}$$

(4.20)

Thus, in order to determine the most appropriate fusion method these five popular methods such as PCA, DWT, SWT, Ehlers and SR have been attempted, experimented and evaluated with the mentioned metrics. Having studied the performance of the state of art, an enhancement through sparse coding (EDSR) is formulated and thereby the fusion process is improvised to yield better result for change detection.