

**THESIS ON**

**EFFICIENT IMAGE FUSION**  
**USING DWT**

**Submitted by**

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# Certificate



This is to certify that the project work in the thesis on “***Efficient Image Fusion using DWT***” by **Saurabh Sahu**, bearing roll number **111EC0190**, is an authentic record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering.

Neither this thesis nor any part of it has been submitted for any kind of fulfillment of degree or any academic award elsewhere.

**Prof. A.K. Sahoo**

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## Acknowledgment

This dissertation, though an individual work, has benefited in various ways from several people. Whilst it would be simple to name them all, it would not be easy to thank them enough.

The enthusiastic guidance and support of Prof. A.K. Sahu inspired me to stretch beyond my limits. His profound insight has guided my thinking to improve the in my work. My solemnest gratefulness to him.

Finally, my heartfelt thanks to my family and friends for their unconditional love and support. Words fail me to express my gratitude to my beloved parents, who sacrificed their comfort for my betterment.

**Saurabh Sahu**

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## Abstract

The method of combining important details from two or more source images into a final fused image is known as **Image Fusion**. When compared to any of the other input images, our fused output image will have more detailed information in it. The objective of image fusion is to obtain the most desirable data from each image.

Multi sensor image fusion algorithm based on three different fusion techniques have been discussed in this paper. Those are "Pixel Level Iteration", "Directional Discrete Cosine Transform (DDCT)", and "Discrete Wavelet Transform (DWT)".

The outcomes are additionally outfitted in picture and table organization for near examination of above methods. This paper shows the three distinctive picture combination strategies and there relative results, as the routine combination methods Direct Pixel Iteration and Discrete Cosine Transform has a few downsides. The similar study presumes that Discrete Wavelet Transform is one of the best and most effective algorithm for Image Fusion. In this thesis, Discrete Wavelet Transform based two calculations are proposed, these are Maximum Intensity Replacement and Band Averaging Method.

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## Objective:

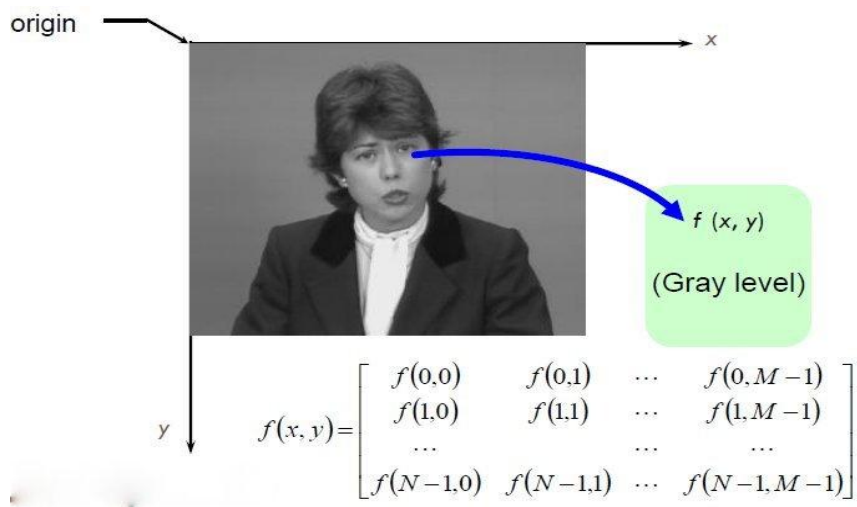
The main objective of this intended project is to develop and simulate a parallel algorithm to implement various Image Fusion Techniques using different Image Fusion rules. Further, test these Image Fusion techniques and obtain all the quality metric of these technique to test the quality index of each technique with respect to each rules. Finally identify the most efficient and effective method for Image Fusion. Also find the best case and worst case scenarios for each of the implemented Image Fusion Techniques.

Finally develop and simulate an effective algorithm for Image Fusion.

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# Introduction

**Image:** Image is a 2D function,  $f(x,y)$  where amplitude of  $f(x,y)$ . The point  $(x,y)$  have been shown in the figure below. Origin of any image for the evaluation of  $x$  and  $y$  is as shown in the figure below. That is the top left corner pixel of the image is always taken as the origin and the positive  $x$ -axis towards the left and the positive  $y$ -axis towards to bottom of the image. Hence, now  $F(x,y)$  gives the value of intensity or R-G-B-A values of the pixel at the point  $(x,y)$  as shown in the figure.



There are following different types of images:

1. **Grayscale Image:** In this type of image, the function  $f(x,y)$  gives the shade intensity at the pixel present in the position of  $(x,y)$ . It is generally used in black and white images but colour images have the same intensity levels that is the average of the intensities of the R-G-B values.







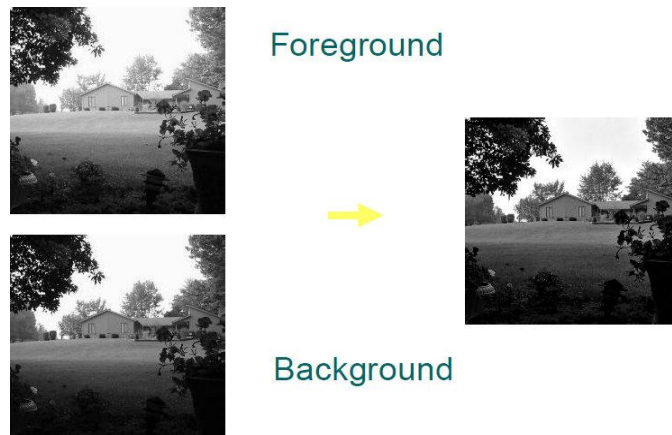
- Image Morphing
- Face Recognition.
- Image Fusion and so on.

**Image Fusion:** The method of joining important data from two or more source images into a final fused image. The subsequent picture would be more instructive and detailed when compared to any of the given source images.

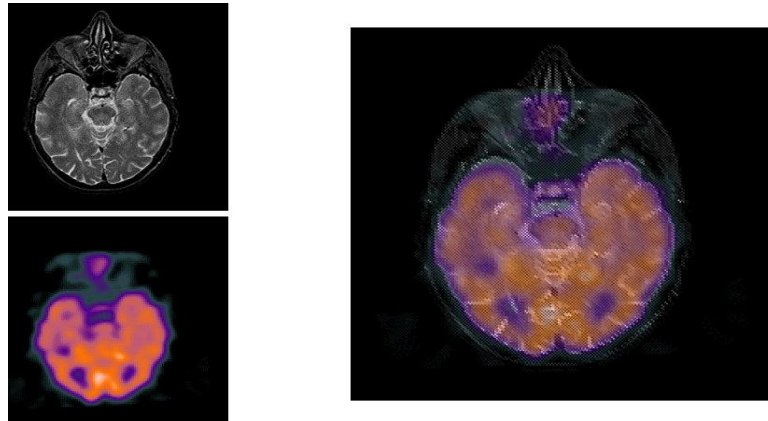
Any bit of data bodes well just when it has the capacity pass on the substance over. The clarity of data is critical. By the procedure of picture combination the great data from each of the given pictures is melded to frame a resultant picture whose quality is better than any of the information pictures.

There are basically following four different types of image fusion:

- **Multi-view Fusion:** This form of image fusion include fusion of two or more source images that are takes at the same time and that have that same modality but different source images are to be taken from different places or in different background conditions.



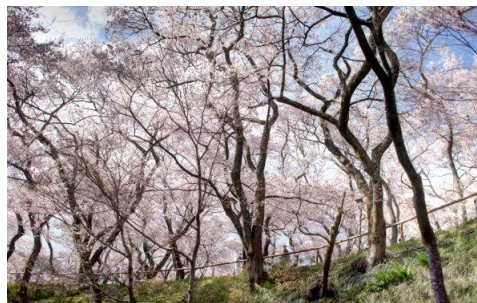
- **Multimodal Fusion:** This type of image fusion include fusion of two or more source images that include the object and the images are taken under different modalities. This form of image fusion has its applications in most of the medical fields like for PET, CT, MRI etc.



- **Multi-temporal Fusion:** This type of image fusion includes fusion of two or more source images that are taken under same modality and of the same scene but at a different time. Eg:



Fused image:



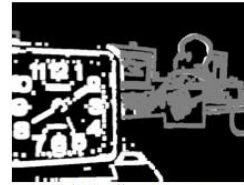
- **Multi-focus Fusion:** This type of image fusion includes fusion of two or more source images where each source image is divided into areas such that every pixel is in focus at least in any one of the source images.



(a) Focus at near



(b) Focus at far



(c) Gradient source



(d) Auto-focus result



(e) Optimal fusion result

# Applications:

Its **main application categories** are:

1. Image Fusion with different viewpoints – multi-view
2. Image Fusion with different times – multi-temporal
3. Image Fusion with different modalities – multi-modal
4. Scene to model registration

**Image Fusion has its applications in wide range of fields:**

- Magnetic Resonance Image (MRI)
  - Multiple images from satellite are fused to obtain a focused image.
  - Image restoration of blurry images
  - Computed Tomography(CT)
  - Image reconstruction
  - Correction of images from different modalities
  - Object identification.
  - Change detection.
  - Positron Emission Tomography(PET)
  - Remote Sensing
  - Pan-Sharpening in photoshop
  - Radiology and radiation oncology
  - Intensity Modulated Radiation Therapy(IMRT)
-

## Fusion Techniques:

- **Pixel level iteration:** In this technique, fusion rules are directly applied on the function  $F(x,y)$  where, the function  $F(x,y)$  gives 3 output values that are the colour intensities of the corresponding pixel at  $(x,y)$ . These values are the Red-Green-Blue intensity value. Two major fusion rules have been used in this project under direct pixel level iteration technique. Those are:
    1. Weighted Pixel Averaging.
    2. Maximum Pixel Intensity method.
  - **Directional Discrete Cosine Transform based Image Fusion:** In this technique, initially Directional Discrete Cosine Transform is performed in the function  $F(x,y)$  where, the function  $F(x,y)$  gives the pixel intensities of the corresponding pixel at  $(x,y)$ . Now, different fusion rules are applied to the directional discrete cosine transform coefficients. Three major fusion rules have been used in this project under Directional Discrete Cosine Transform image fusion technique. Those are:
    1. DDCTavg
    2. DDCTmax
    3. DDCTek
  - **Discrete Wavelet Transform based Image Fusion** In this technique at the initial step, Discrete Wavelet Transform is performed in the function  $F(x,y)$  where, the function  $F(x,y)$  gives the pixel intensities of the corresponding pixel at  $(x,y)$ . Now, different fusion rules are applied to the Discrete Wavelet transform coefficients. Three major fusion rules have been used in this project under Directional Discrete Cosine Transform image fusion technique. Those are:
    1. DWTavg
    2. DWTmax
-

## Pixel Level Iteration:

From the 2D function,  $F(x,y)$  where the amplitude of  $F(x,y)$  gives the value of intensity or R-G-B-A values of the pixel at the corresponding position of  $(x,y)$ . In this technique, fusion rules are directly applied on the function  $F(x,y)$ . Two major fusion rules have been used in this project under direct pixel level iteration technique. Those are:

1. Weighted Pixel Averaging.
2. Maximum Pixel Intensity method.

### Weighted Pixel Averaging:

The intensity value of the pixel  $P(i, j)$  of each of the source image that is  $A(x,y)$  and  $B(x,y)$  is to be taken and added according to the weighted values ' $W_a$ ' for first source image and ' $W_b$ ' for the second source image. The corresponding Pixel value was assigned the value of the summation of the weighted intensities.

$$P(x, y) = A(x,y)*W_a + B(x,y)* W_b$$

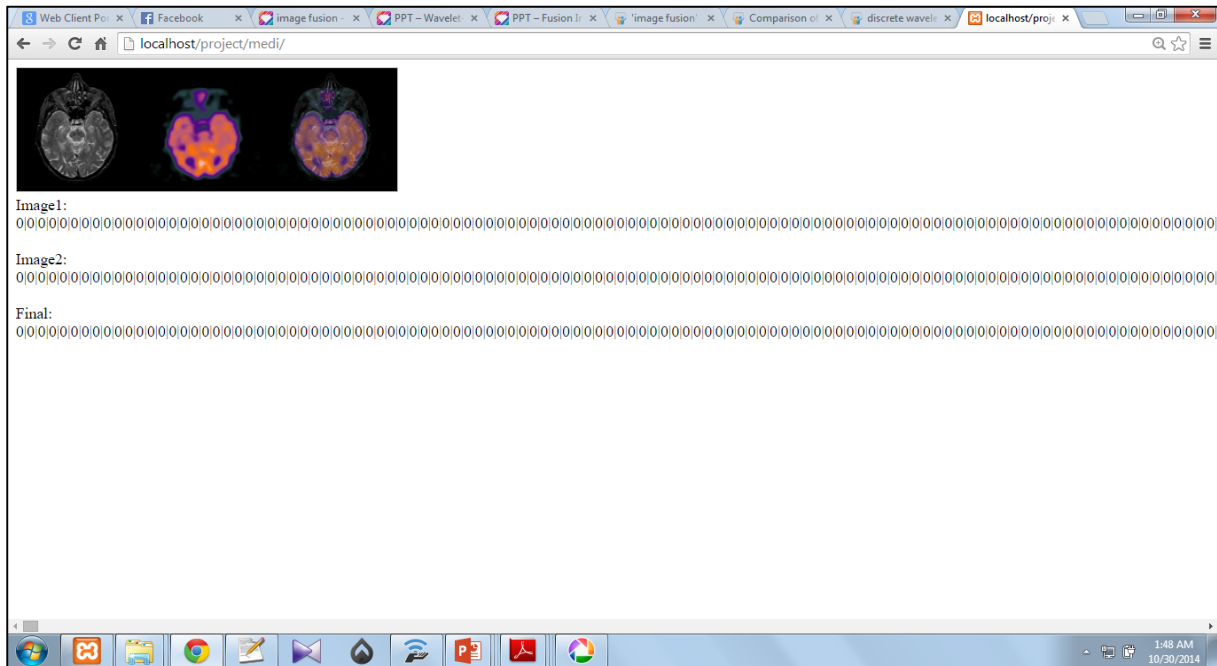
Where  $W_a, W_b$  are scalars and for simplicity we take the values of  $W_a$  and  $W_b$  to be 0.5 each. That is we take the average of the intensity values of each pixel and assign it to the new image to be generated.

It is the most simple and relatively efficient method of image fusion. Any noise in the source image is suppressed in this method as noise in one of the source image is nullified by the pixel values of the other image.

This type of image fusion rule is effective for multi-temporal image fusion which includes fusion of two or more source images of the same scene where they are taken under same modality but at different time

### Implementation and Results:

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### Maximum Intensity technique:

The more noteworthy the pixel values the all the more in center the picture. This calculation picks the in-center locales from every data picture by picking the best esteem for every pixel. The estimation of the pixel  $P(i,j)$  of every picture is taken and contrasted with one another. The best pixel quality is assigned to the relating pixel.

The pixel having the maximum intensity value retains a sharper, more informative value and is taken to be the most relevant pixel compared to the pixel of the other source images. That is, greater the pixel value of the image, the greater is the focus on it with respect to other source images.

The intensity value of the pixel at  $(x,y)$  from all the source images are compared and the greatest of all these values are assigned to the corresponding pixel at  $(x,y)$  of the output to generate the fused image.

This Image Fusion rule is most effective for multi-focus image fusion which includes fusion of two or more source images where each source image is divided into areas such that every pixel is in focus at least in any one of the source images.

## Implementation and Results:

localhost/project/rgb/ x localhost/project/gray/ x localhost/project/invert/ x localhost/project/averag... x localhost/project/max/ x

localhost/project/max/




Image1:  
139|67|65|65|64|62|58|60|61|61|60|60|59|60|63|64|65|67|67|65|66|66|65|69|69|71|70|72|72|73|71|74|74|78|77|79|81|82|84|87|87|91|94|103|112|117|119|116|110|104|106|105|105|105|103|102|102|10

Image2:  
164|160|158|151|135|131|127|129|133|131|127|131|123|127|126|126|124|121|123|122|121|124|123|124|125|127|123|124|120|126|127|130|130|129|134|133|132|134|135|139|149|155|155|163|167|1

Final:  
164|160|158|151|135|131|127|129|133|131|127|131|123|127|126|126|124|121|123|122|121|124|123|124|125|127|123|124|120|126|127|130|130|129|134|133|132|134|135|139|149|155|155|163|167|1

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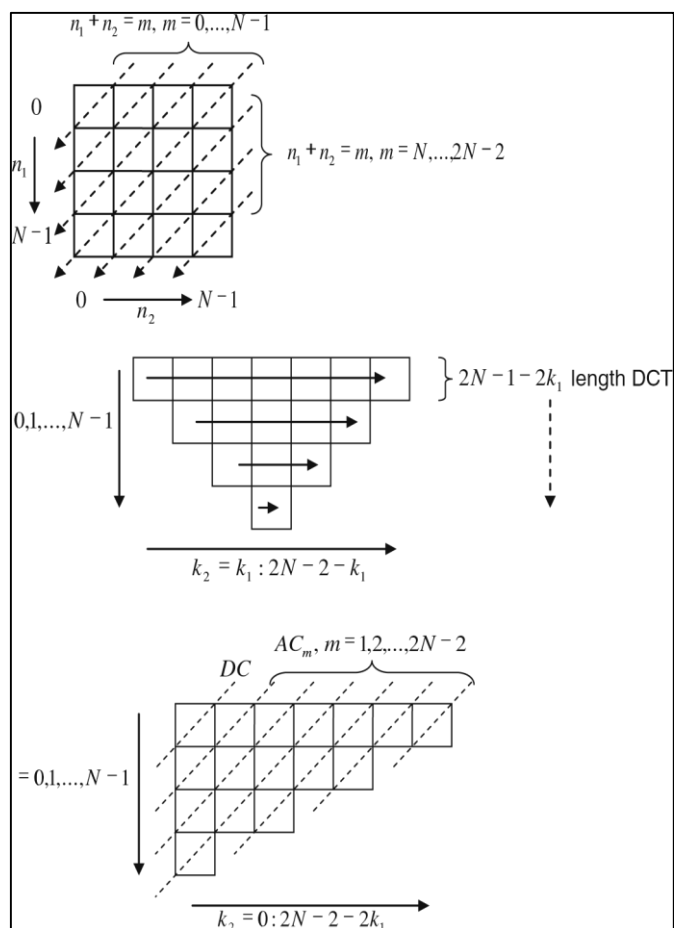


## Directional Discrete Cosine Transform:

The input images were divided into non-overlapping square blocks and the fusion process was carried out on the corresponding blocks. The algorithm works in two stages. In first stage, modes 0 to 8 were performed on images to be fused. For each mode, the coefficients from the images to be fused are used in the fusion process. The same procedure is repeated for other modes. Three different rules are used in this fusion process viz: 1. Averaging the corresponding coefficients (DDCTavg), 2. Choosing the corresponding frequency band with maximum energy (DDCTek) and 3. Choosing the corresponding coefficient with maximum absolute value (DDCTmax) between the images. After this stage, there are eight fused images, one from each mode. In second stage, these eight fused images are fused using PCA.

The computerized pictures are showing on a screen promptly after they are caught. There are two speak to sorts for computerized picture that is spatial area or frequency space. Spatial area picture can be acknowledges through our human eyes, frequency area utilization to investigation of spatial space A Discrete Cosine Transform (DCT) is a critical change in image transforming. It is constantly used to express an arrangement of limited information focuses as far as an entirety of cosine capacities swaying at distinctive frequencies. Huge DCT coefficients are amassed in the low recurrence district; thus, it is known to have fabulous vitality minimization properties. Discrete Cosine Transformation (DCT) are critical to various applications in science, building and in pictures pack, as MPGE, JVT, and so on.

Performance of these algorithms were compared using fusion quality evaluation metrics such as root mean square error, quality index (QI), spatial frequency, fusion quality index (FQI).



### Directional discrete cosine transform

The 1D DCT  $X(k)$  of the sequence  $x(n)$  having length  $N$  is defined to be:

$$X(k) = \alpha(n) \sum_{n=0}^{N-1} x(n) \cos\left(\frac{\pi(2n+1)k}{2N}\right), \quad 0 \leq k \leq N-1$$

$$\text{Where, } \alpha(k) = \begin{cases} \sqrt{\frac{1}{N}} & k = 0 \\ \sqrt{\frac{2}{N}} & k \neq 0 \end{cases}$$

The inverse DCT is defined to be:

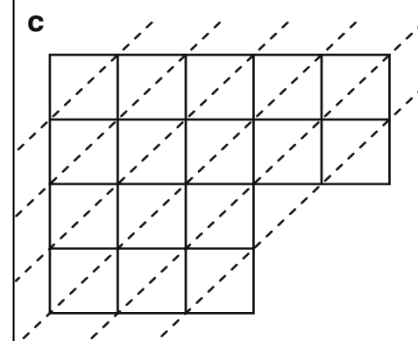
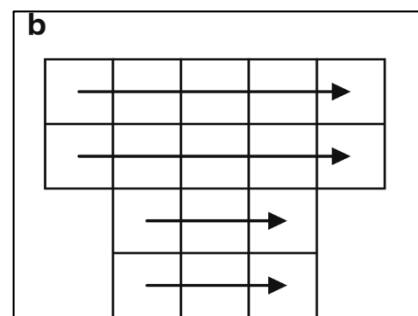
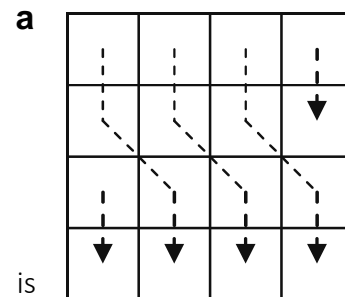
$$x(n) = \sum_{k=0}^{N-1} \alpha(k) X(k) \cos\left(\frac{\pi(2n+1)k}{2N}\right), \quad 0 \leq n \leq N-1$$

### Mode 3 (diagonally down-left mode):

Consider an  $N \times N$  image block as shown in Fig. 1D DCT is performed along diagonally down-left direction that is for all diagonal line (shown as dotted line) with  $n_1+n_2=m$ ,  $m=0, 1, \dots, 2N-2$ . From Fig., it is known that there are  $2N-1$  lines that are diagonal down-left 1D DCT's to be performed, their lengths are  $N_m=[1,2,\dots,N-1,N,N-1,\dots,2,1]$  and coefficients are arranged in column vectors as shown in Fig. The first row in Fig. contains DC components followed by AC components. Second 1D DCT is performed horizontally (row wise as indicated by arrow line as shown in Fig.) and these coefficients are then pushed horizontally to the left as shown in Fig.

### Mode 5 (Directional DCT for the vertical-down mode)

Consider  $N \times N$  image block as shown in Fig a. Perform 1D DCT along the vertical-right direction (shown as dotted arrows) and the coefficients as shown in Fig b. On these coefficients, 1D DCT is performed horizontally and these coefficients are then pushed to the left as shown in Fig c.



## Other Modes

Mode	Direction	Procedure
0	Vertically down	Apply 1D DCT column wise and then apply 1D DCT horizontally (each row)
1	Horizontally right	Transpose the image block, apply mode 0 procedure
3	Diagonally down-left	In Mode 3
4	Diagonally down-right	Flip the image block horizontally and then apply mode 3 procedure
5	Vertical-right	Explained in Mode 5
6	Vertical-right	Transpose the image block, apply mode 5 procedure
7	Vertical-left	Flip the image block horizontally and then apply mode 5 procedure
8	Horizontal-up	Transpose the image block, Flip the block horizontally and then apply mode 5 procedure

## Principal Component Analysis (PCA):

1. Organize the information into segment vectors. The subsequent framework Z is of measurement  $n \times 8$ .
  2. Compute the exact mean along every section. The exact mean vector M has a measurement of  $8 \times 1$ .
  3. Subtract the exact mean vector M from every section of the information framework Z.
  4. Find the covariance grid C of S i.e.  $C = XT X$
-

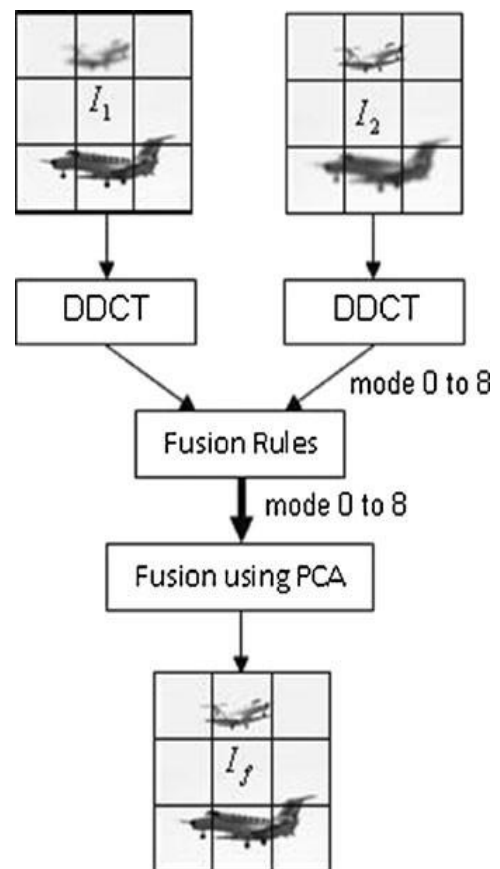
5. Sort the eigenvectors  $V$  and eigenvalue  $D$  of  $C$  in decreasing order.
6. Consider the first section of  $V$  which compares to bigger eigenvalue to register to compute the principal components as:

$$PC_1 = \frac{V(1)}{\sum V}, PC_2 = \frac{V(2)}{\sum V}, \dots, PC_8 = \frac{V(8)}{\sum V}$$

### Algorithm:

In this section we will perform three different techniques for image fusion by DCT method. All the images that is to be fused is divided into non-overlapping blocks. These blocks are made of size  $N \times N$  as shown in Fig. DDCT coefficients are calculated for each of these blocks and corresponding fusion rules are applied to get the fused DDCT coefficients of each block. Inverse DDCT is then applied over the fused coefficients so as to produce the fused block. The procedure is repeated for each block.

The accompanying combination tenets are utilized as a part of picture combination process. Let the  $X_1$  be the DDCT coefficients of picture square from picture  $I_1$  and likewise let the  $X_2$  be the DDCT coefficients of picture piece from picture  $I_2$ . Expect the picture square is of size  $N \times N$  and  $X_f$  be the combined DDCT coefficients



### DDCTavg

Now, for the DDCT coefficients of the final fused image, we use these DDCT coefficients of the source images. Weighted average of the DDCT coefficients of the source image is found and this weighted average is assigned to the corresponding DDCT coefficient band of the final fused image.

For simplicity we use the values of the weighted graphs that is  $W_a$  and  $W_b$  to be 0.5 each. That is we are now taking the mathematical average of the DDCT coefficients of all the source image. This is given by the equation below:

$$X_f(k_1, k_2) = 0.5(X_1(k_1, k_2) + X_2(k_1, k_2))$$

Further Inverse Discrete Cosine Transform is performed to these coefficients to get the desired fused image.

### DDCTmax

Now, for the DDCT coefficients of the final fused image, we compare the DDCT coefficients of all the source images. The greatest values of the DDCT coefficients of the source image is found and this value is assigned to the corresponding DDCT coefficient band of the final fused image.

For an object that is better focused in the image, we will have sharp edge or corner detection that the bands where the object is not in focus. So using this fundamental rule we use the maximum DDCT values as maximum DDCT values correspond to the better and sharp values for edge or corner detection.

This is given by the equation below:

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & |X_1(k_1, k_2)| \geq |X_2(k_1, k_2)| \\ X_2(k_1, k_2) & |X_1(k_1, k_2)| < |X_2(k_1, k_2)| \end{cases}$$

Where,  $k_1, k_2=1,2,3,\dots,N-1$

Further Inverse Discrete Cosine Transform is performed to these coefficients to get the desired fused image.

### DDCTek

For this image fusion rule, we need to calculate the energy of the DDCT coefficients. The energy of a DDCT coefficients is given by the  $E_j$ . The quantity  $E_j$  is the mean amplitude over a  $j^{\text{th}}$  spectral band and is computed as

$$E_j = \frac{\sum_{j=t+p} |X(p, t)|}{Y}$$

$$\text{Where, } Y = \begin{cases} j + 1 & j < N \\ 2(N - 1) - j + 1 & j \geq N \end{cases}$$

This image fusion rule works in the principle that the band having the maximum energy level for the DDCT coefficients is having the sharper image quality. This is attributed to the fact that the the position of the image where there is actual focus, we find there the energy to be more. So to identify the image with sharper image qualities, we compare the energy coefficients of the DDCT bands.

That for a particulat band, the maximum energy from all the source images is taken and assigned to the final coefficients of the image. Further inverse Discrete Cosine Transform is performed to these coefficients to get the desired fused image.

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & E_{j1} \geq E_{j2} \\ X_2(k_1, k_2) & E_{j1} < E_{j2} \end{cases}$$

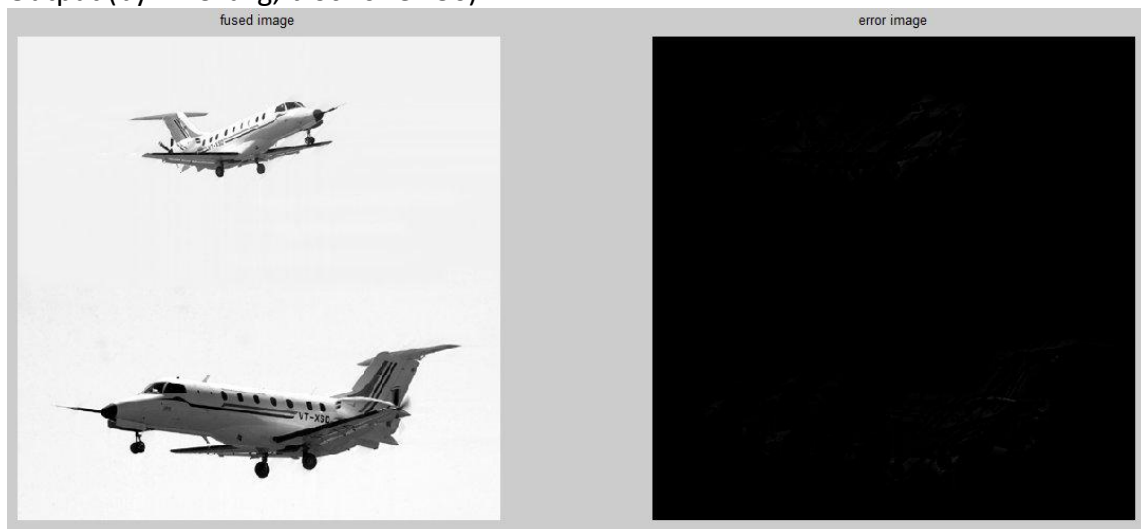
$$\text{Where, } k_1, k_2 = 1, 2, 3, \dots, N - 1$$

### Implementation & Output (DDCT):

Input Image:



Output (by DDCTavg, block size 256):



Output (by DDCTmax, block size 256):



Output (by DDCTek, block size 256):



Reference Image:



### Performance Metrics (DDCT):

**Root Mean Square Error:** RMSE is figured as the root mean square of the comparing pixels in the reference picture  $I_r$  regarding the melded picture  $I_f$ .

$$RMSE = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I_r(i,j) - I_f(i,j))^2}$$

Root Mean Square Error will be practically zero when the reference image and the fused images exactly the same. It will increase gradually as the dissimilarities increases. These dissimilarities account for the error factor in the image. As to how far the obtained output and the actual output differ.

We can be observed that the final fused image retains most of the useful data from all the input images. The performance for evaluating the image fusion output by DCT method for various block size are shown in Table below.

Fusion Rule	4×4	8×8	16×16	32×32	64×64	128×128	256×256
DDCTav	9.42	9.42	9.42	9.42	9.42	9.42	9.42
DDCTmax	8.19	6.51	4.91	3.89	3.36	2.76	2.13
DDCTek	7.97	6.14	4.54	3.34	2.78	2.13	1.67



From the above fused images and the obtained values of Root Mean Square Errors in the quality measure table, it can be concluded that DDCTavg based fusion rule performs Image Fusion. But the error factor in this rule is quite high as compared to the error values of DDCTmax and DDCTek. So DDCTek based image fusion rule provides us better quality fused images than DDCTavg and DDCTmax.

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## Discrete Wavelet Transform based image fusion:

Previously fusion techniques based on “Direct Pixel Iteration” and “Discrete Cosine Transform” have been performed. Although these methods successfully perform Image Fusion to considerable efficiencies, it has been found that these fusion techniques perform well spatially but they tend to introduce spectral distortion.

To overcome this problem we now focus on the fusion techniques based on **Discrete Wavelet Transform (DWT)**. Discrete Wavelet transform is the most popular method of the time and frequency transformations and is widely used in various image processing projects including Image Fusion.

**Wavelet Transform:** A wavelet series is simply a representation of any complex or real valued function by some orthonormal series obtained by a wavelet. In linear algebra based math, two vectors in an internal item space are orthonormal on the off chance that they are orthogonal and unit vectors. An arrangement of vectors structure an orthonormal set if all vectors in the set are commonly orthogonal and all of unit length. An orthonormal set which shapes a premise is called an orthonormal premise.

**Continuous Wavelet Transform:** Before we go into discrete wavelet transform let us look in for a case with continuous input signal. For a continuous input signal given by  $X(t)$ , the Continuous Wavelet Transform of  $X(t)$  is defined as:

$$X_w(a, b) = \frac{1}{\sqrt{b}} \int_{-\infty}^{\infty} X(t) \psi\left(\frac{t-a}{b}\right) dt$$

Where,  $b$  is the scaling factor which is set as per requirement and  $a$  is any real number. The mother wavelet is designed as such CWT is reversible.

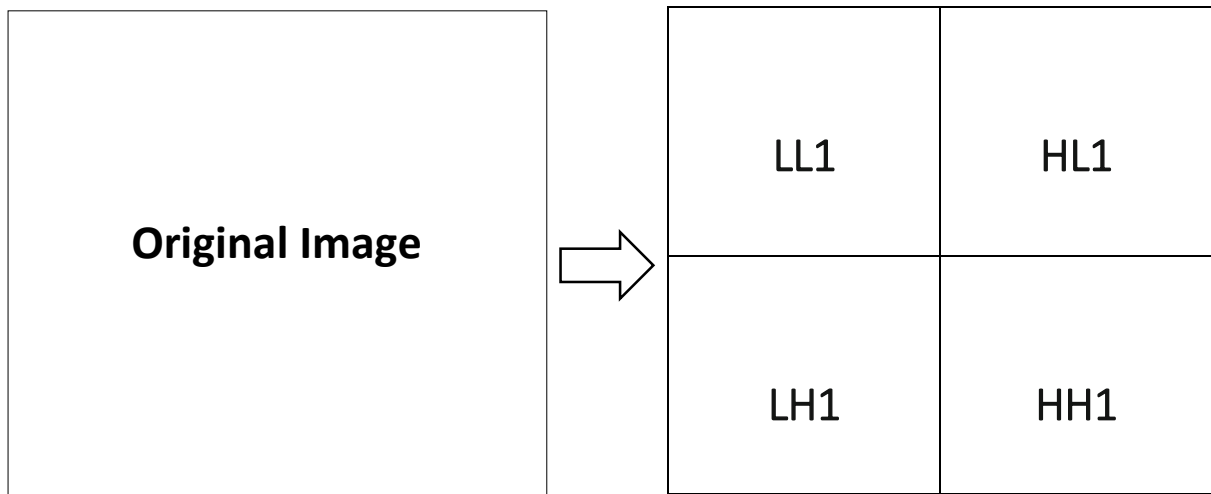
**Discrete Wavelet Transform:** Mathematics of a Continuous Wavelet Transform is finely deducible. But for an image the input cannot be a continuous signal. For image Processing we always have a discrete signal that is mostly obtained by the pixel intensity values.

Now, to work with discrete pixel intensity values of an image, we define Discrete Wavelet Transform. A wavelet transform in which the wavelets or the input function is discretely sampled.

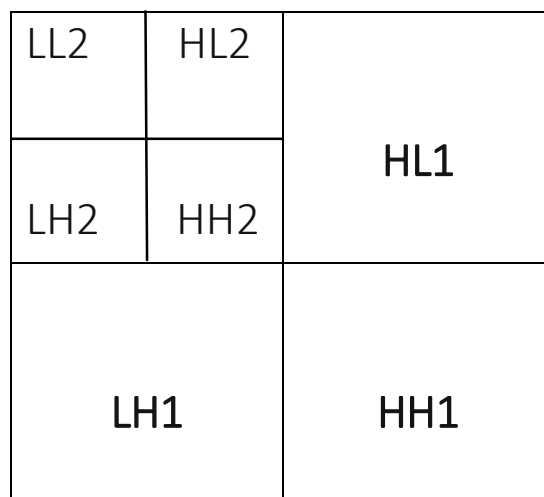
As compared to other wavelet transformations, the advantage of discrete wavelet transform over Fourier transforms or any other transform is that of temporal resolution. That is, while other transforms only capture the location details, the Discrete Wavelet Transform captures both the location and frequency information.

The Discrete Wavelet Transform likewise changes over the image from the spatial domain to frequency domain. The picture is separated by horizontal and vertical lines and gives us the first-order of DWT, and the picture can be differentiated with four sections those are LL1, LH1, HL1 and HH1. In extra, those four sections are represent to four frequency region in the picture. For the low- frequency domain, LL1 is sensitive to human eyes. Whereas In the frequency domains LH1, HL1 and HH1 have more detailed information.

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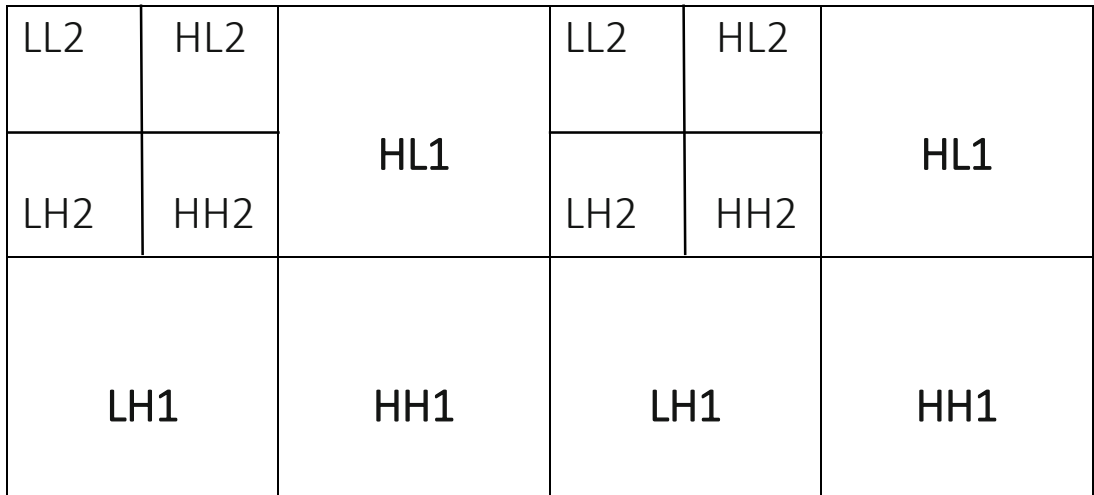
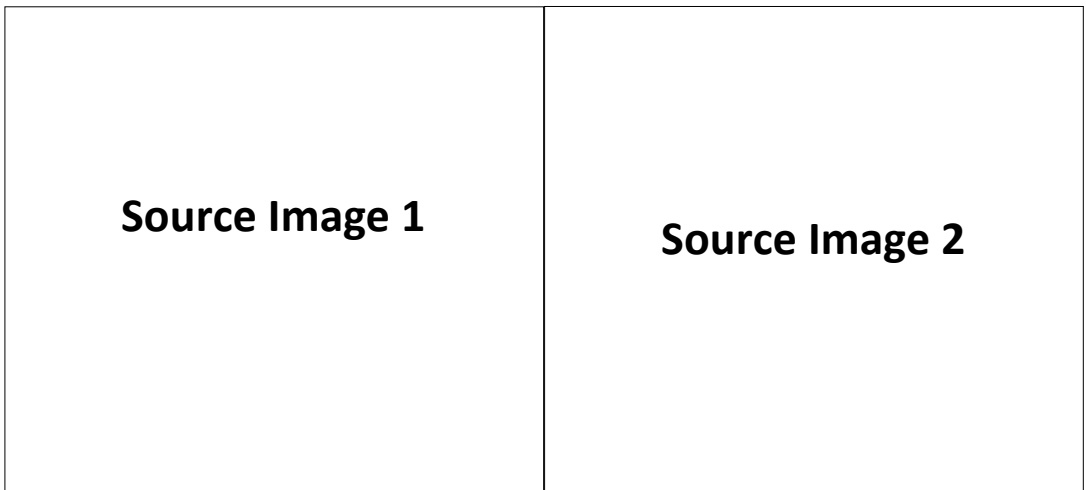


1 Level DWT



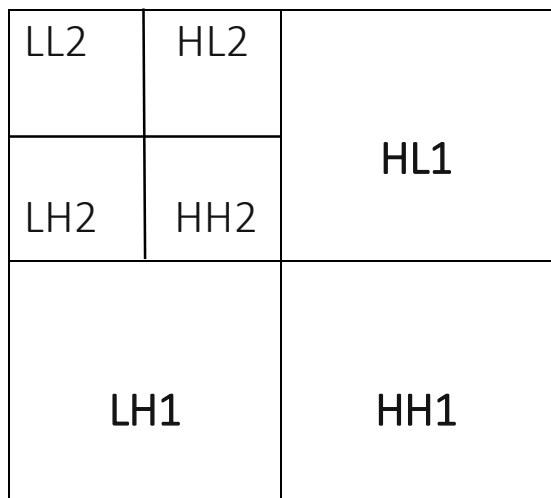
2 Level DWT

**Process Flow:** First, Discrete Wavelet transform is performed on all the input images to obtain the fusion decision map. This is done based on different sets of fusion rules. Fused wavelet coefficient map is to be constructed from the coefficients of the wavelet from the input images in accordance to the fusion decision map. Now, the final fused image is generated by the method of inverse wavelet transform.

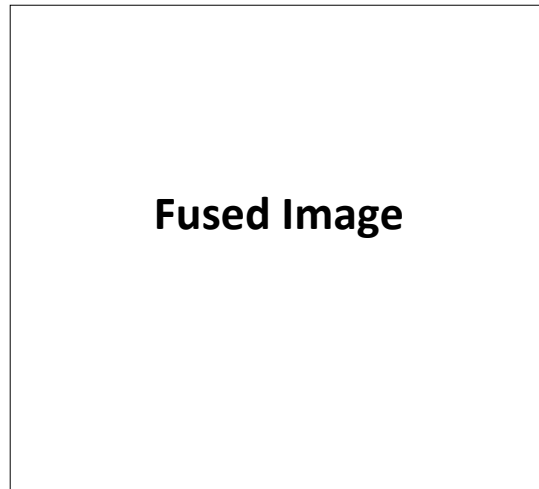


Coefficient Map 1

Coefficient Map 1

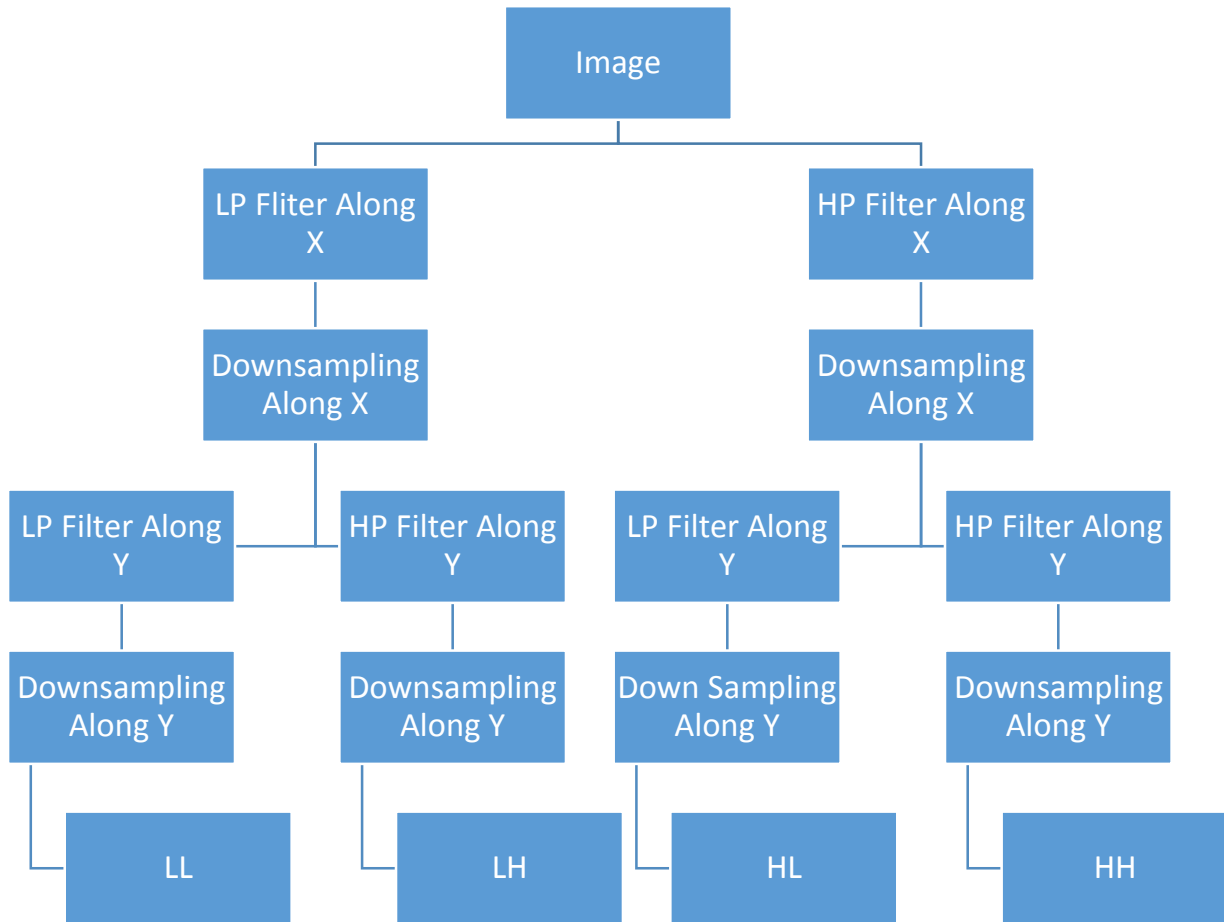


Fused Coefficient Map



### DWT Decomposition:

In discrete wavelet transform decomposition, the channels are exceptionally planned so that progressive layers of the pyramid just incorporate points of interest which are not effectively accessible at the first levels. The DWT deterioration utilizes a course of uncommon low pass and high-pass channels and a sub-inspecting operation. The yields from 2D-DWT are four images having size equivalent to a large portion of the measure of the first image. So from first source image we will get LLa, HLa, LHa, HHa pictures and from second data picture we will get LLb, HLb, LHb, HHb pictures. LH implies that low-pass channel is connected along x and took after by high pass channel along y. The LL picture contains the close estimation coefficients. LH picture contains the level point of interest coefficients. HL picture contains the vertical point of interest coefficients, HH contains the corner to corner subtle element coefficients. The wavelet change can be performed for different levels. The following level of disintegration is performed utilizing just the LL picture. The outcome is four sub-pictures each of size equivalent to a large portion of the LL picture size.



### Fusion Rules:

#### 1. Image fusion using Maximum Pixel replacement:

For the DWT coefficients of the final fused image, we compare the DWT coefficients of all the source images. The greatest values of the DWT coefficients of the source image is found and this value is assigned to the corresponding DWT coefficient band of the final fused image.

For an object that is better focused in the image, we will have sharp edge or corner detection that the bands where the object is not in focus. So using this fundamental rule we use the maximum DWT values as maximum DWT values correspond to the better and sharp values for edge or corner detection.

The Following Steps are involved in this fusion rule:

Take the pixel with the greatest value of the two wavelet bands that is  $HH_a$  and  $HH_b$ , and substitute it in  $HH_n$ .

Take the pixel with the greatest value of the two wavelet bands that is HLa and HLb, and substitute it in HLn.

Take the pixel with the greatest value of the two wavelet bands that is LHa and LHb, and substitute it in LHn.

Take the pixel with the greatest value of the two wavelet bands that is LLa and LLb, and substitute it in LLn.

Hence, we will get LLn,HLn,LHn and HHn as new coefficients of the fused image.

Take Inverse DWT of the obtained coefficients.

Generate the fused Image and show in output.

## 2. Image Fusion using Pixels Averaging:

Now, for the DDCT coefficients of the final fused image, we use these DDCT coefficients of the source images. Weighted average of the DDCT coefficients of the source image is found and this weighted average is assigned to the corresponding DDCT coefficient band of the final fused image.

For simplicity we use the values of the weighted graphs that is  $W_a$  and  $W_b$  to be 0.5 each. That is we are now taking the mathematical average of the DDCT coefficients of all the source image.

The Following Steps are involved in this fusion rule:

Take the weighted average values of the two bands that is HHa and HHb, and substitute it in HHn .

Take the weighted average values of the two bands that is HLa and HLb, and substitute it in HLn.

Take the weighted average values of the two bands that is LHa and LHb, and substitute it in LHn.

Take the weighted average values of the two bands that is LLa and LLb, and substitute it in LLn.

Hence, we will get LLn,HLn,LHn and HHn as new coefficients of the fused image.

Take Inverse DWT of the obtained coefficients.

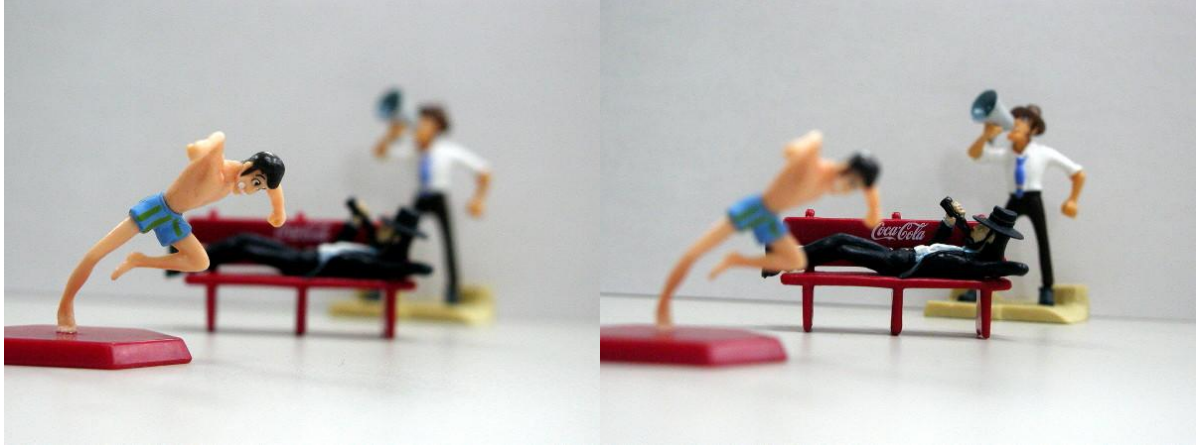
Generate the fused Image and show in output.

### Algorithms:

- Accept the images to be fused.
  - Resize both the images to 256X256.
  - Convert it to grey scale image.
  - Convert it to double precision format.
  - Generate discrete wavelet transform of the source images.
  - Let, first image out bands be Lla, Hla, Lha, Hha and image out bands for the second image be Llb, Hlb, Lhb, Hhb.
  - Apply any desired fusion rules to obtain the final fused image having the out bands as HLLn, Hln, Lhn, Hhn.
  - Take inverse discrete transform of the bands to obtain the final required image.
-

## Experiments & Output (DWT):

Input Image (DWTmx):



Output Image:



Input Image (DWTav):





Input 1

Input2



Input3



Output Image:

## Quality Measures:

**Root Mean Square Error:** RMSE is figured as the root mean square of the comparing pixels in the reference picture  $I_r$  regarding the melded picture  $I_f$ .

$$RMSE = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I_r(i,j) - I_f(i,j))^2}$$

Root Mean Square Error will be practically zero when the reference image and the fused images exactly the same. It will increase gradually as the dissimilarities increases. These dissimilarities account for the error factor in the image. As to how far the obtained output and the actual output differ.

**Peak Signal to Noise Ratio:** Peak Signal to Noise Ratio, frequently shortened as PSNR, is a building term for the proportion between the greatest conceivable power of a signal and the power of noise that influences the constancy of its representation. Since numerous signals have a wide range, PSNR is normally communicated regarding the logarithmic decibel scale.

PSNR is most generally used to quantify the nature of remaking of project codecs (e.g., for image fusion). The sign for this situation is the first information, and the commotion is the lapse presented by the power of the signal. At the point when contrasting power codecs, PSNR is a close estimation to human view of remaking quality. Despite the fact that a higher PSNR for the most part shows that the recreation is of higher quality, but in the case of image fusion, it is not so. So it can be used as a quality measure for this case.

Mathematically it is given by:

$$PSNR = 10 * \log_{10}\left(\frac{peak^2}{MSE}\right)$$

**Average Difference:** It measures the statistical dispersion that is equal to average of the absolute difference in the independent values that are drawn from the probability distribution function. Due to its wide usage, it has become one of the most important quality measure in the image processing field.

It is given by:

$$AD = \frac{1}{\sum_{i=1}^m \sum_{j=1}^n (|A_{ij} - B_{ij}|)}$$

**Normalized Absolute Error:** It is used to quantize how close predictions or forecasts are to the final outcomes. The mean outright lapse is a typical measure of gauge mistake in time arrangement investigation, where the expressions "mean supreme deviation" is in some cases utilized as a part of perplexity with the more standard meaning of mean total deviation. The same perplexity exists all the more by and large.

It is given by:

$$NAC = \frac{\sum_{i=1}^m \sum_{j=1}^n (A_{ij} - B_{ij})}{\sum_{i=1}^m \sum_{j=1}^n (A_{ij})^2}$$

Fusion Rules	Peak Signal to Noise Ratio	Normalized Absolute Error	Root Mean Square Error	Maximum Difference	Average Difference
Pixel Level Iteration	35.8316	0.0086	10.8669	29	0.9573
DCTav	39.7047	0.0042	5.4544	28.2000	0.5212
DWTav	41.6429	0.0038	4.4544	27.5000	0.4212
DWTmx	46.3594	0.0021	1.5036	21.4172	0.2329

## Conclusion:

In this paper, relevant information is combined from two or more source images to form a single output image. Resulting image was found to be more informative and detailed than any of the other source images. In this paper, there are three different image fusion techniques used.

1. Pixel Level Iteration
2. Directional Discrete Cosine Transform
3. Discrete Wavelet Transform.

From the above fused images and the obtained values of errors in the quality measure table, it can be concluded that Pixel Level Iterations and Discrete Cosine Transform based fusion technique may be used for fields where it does not require high precision and quality. Whereas Discrete Wavelet Transform based image fusion technique provides us better quality fused images than Pixel Level Iteration and Discrete Cosine Transform based techniques.

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## Reference:

- [http://en.wikipedia.org/wiki/Image\\_processing](http://en.wikipedia.org/wiki/Image_processing)
  - [http://en.wikipedia.org/wiki/Image\\_fusion](http://en.wikipedia.org/wiki/Image_fusion)
  - Jan Flusser, Filip Šroubek, and Barbara Zitov', Institute of Information Theory and Automation Academy of Sciences of the Czech Republic "Image Fusion: Principles, Methods, and Applications",  
[http://staff.utia.cas.cz/sroubekf/papers/EUSIPCO\\_07\\_fusion\\_tut.pdf](http://staff.utia.cas.cz/sroubekf/papers/EUSIPCO_07_fusion_tut.pdf)
  - <http://link.springer.com/article/10.1007/s12596-013-0148-7/fulltext.html>.
  - Matthias Berth<sup>1</sup>, Frank Michael Moser<sup>1</sup>, Markus Kolbe<sup>1</sup> and Jörg Bernhardt, Institute of Microbiology, Greifswald University, Jahnstrasse 15, 17487 Greifswald, Germany.
  - <http://link.springer.com/book/10.1007/978-3-642-11216-4>
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