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Research Article

MEDICAL IMAGE FUSION USING CONTOURLET TRANSFORM AND FUSION TOOL TECHNIQUES

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Abstract

The process of achieving single fused image by combining relevant information from more images is image fusion. The resultant image will have more information when compared to the given input images. Image fusion has become a regulation for huge number of applications to derive the formal solutions in many fields like Aerial and Satellite imaging, Medical imaging, Robotic vision, Multi-focus image fusion, Digital camera application etc. Medical image fusion is very much essential for diagnosing diseases efficiently using multidimensional, multi-parameter image types. The objective of this paper is to design a multi modality medical image fusion system using different fusion methods with quantitative analysis. In this system, initially, images having different modalities can be considered as input such as CT (anatomical information) and MRI (functional information). Then the fusion methods viz., Contourlet Transform method, fusion tool methods (Average, Contrast Pyramid, Discrete Wavelet Transform (DWT), Filter-Subtraction-Decimate Pyramid (FSD), Gradient Pyramid, Laplacian Pyramid, Maximum, Minimum, Morphological Pyramid, Principal Component Analysis (PCA), Ratio Pyramid, and Shift Invariant Discrete Wavelet Transform Pyramid (SIDWT)) are applied and further resultant image is analyzed using various quantitative metrics such as Standard Deviation (SD), Entropy (EN), and Power Signal to Noise Ratio (PSNR) for performance evaluation. From the experimental results, it is observed that the Contourlet Transform method perform well than the fusion tool methods are proved through all metrics.

Keywords: Multimodality images; Medical image fusion; Contourlet Transform; Fusion tool; Quantitative metrics.

I. Introduction

In most of the situations image processing applications concurrently require both high spatial and spectral information being in a single image [11] which is most important in medical images. However, the instruments that are used are not that much capable enough in providing the required information by design or of observational constraints. So one of the promising solutions is image fusion. Recently [10], attention towards learning of multimodal medical image fusion has increased due to demand in clinical application.

Medical image fusion helps physicians in examining the features that may not be normally visible in images from different modalities (e.g., MRI-T1 gives greater detail of anatomical structures, whereas MRI-T2 gives greater contrast between normal and abnormal tissues). Medical image fusion combines these contrasting and complimentary features into one fused image to extract more information. In this area of research many approaches are proposed [8] for fusion, such as Filter-Subtraction-Decimate Pyramid (FSD), Gradient Pyramid, Laplacian Pyramid [3], Discrete Wavelet Transform Pyramid (DWT) [12], Shift Invariant Discrete Wavelet Transform Pyramid (SIDWT) [5], Morphological Pyramid [8], Ratio Pyramid, Contrast Pyramid, and so on. All the above methods share one characteristic: each approach has its own limits. For example, Contrast Pyramid method loses too much information from the source images; Ratio Pyramid method produces lots of false information that does not exist in the source images; and Morphological Pyramid method creates many bad edges.

To overcome limitation of all these methods, in this paper Contourlet Transform and Fusion tool medical image fusion methods are proposed. Evaluation of performance of each fusion techniques is based on quantitative metrics such as SD, EN, PSNR [9], [10], [13]. The rest of this paper is organized as follows. In the coming section, system design is summarised and next section describes the experimented results and calculated performance of various methods. Finally conclusion and future work are summarised.

II. System Architectural Design

Images having different modalities can be considered as input such as CT which gives anatomical information and MRI which gives functional information. To get the more information than the input images, the following fusion techniques are proposed Contourlet Transform, and Fusion tool to registered images. Finally the fused images are validated using quantitative analysis.

2.1 Dataset:

The brain images are taken from the same patient at different modality such as CT and MRI (MR-T2 and MR- FLAIR) are used to test the fusion methods.

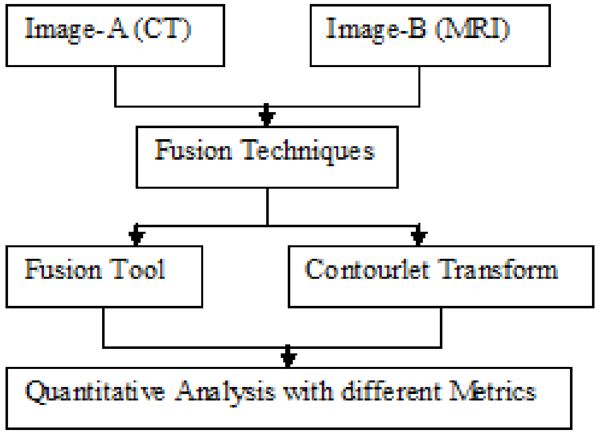


Fig 1: An overall view of system design.

2.2 Fusion Tool

Fusion tool [8] consist of different methods namely Average Method, Contrast Pyramid, DWT Pyramid, Laplacian Pyramid, FSD Pyramid, Gradient Pyramid, Select Maximum and Minimum, Morphological Pyramid, PCA Pyramid, Ratio Pyramid, SIDWT Pyramid. These methods are classified as spatial and transform domain fusion. Former domain approaches are: Average Method, Contrast Pyramid, PCA Pyramid, FSD Pyramid, Gradient Pyramid, Select Maximum and Minimum method, Ratio Pyramid. These methods lead to spatial distortion in the fused image. To overcome the drawback of spatial distortion, transform domain fusion methods are suited are medical images such as Morphological Pyramid, DWT Pyramid, SIDWT Pyramid, Laplacian Pyramid.

2.3 Contourlet Transform

Contourlet transform gets smoothness in a fused image with any two different modalities of images [1, 2]. This region based transformation is implemented in two stages. In the initial stage double filter bank scheme is applied for transformation and in the following stage decomposition is done with fusion rules. Finally the fused image is recovered using reconstruction procedure.

1) Disintergration stage:

The images [1] are disintegrated into only one low-pass and several high-pass subbands in different angles and scales using double filter bank scheme. Low-pass subband is approximation of the original image, while highpass subband shows high frequency in different direction.

2) Fusion Stage:

The decomposed subbands of transformation stage are combined using Lowpass and Highpass Fusion rules.

a) Lowpass subband fusion: The coefficients in the coarsest scale subband a_j represent the approximation component of the source image. Here [1] local energy contour domain developed as the measurement, selection and averaging are used to compute final coefficient.

First to calculate the local energy $E(x,y)$ centring the current coefficient in the approximate subband a_j which is

$$E(x,y)=\sum_m \sum_n a_j(x+m,y+n)^2 W_L(m,n) \tag{1}$$

Where (x,y) denotes the current contourlet coefficient, $W_L(m,n)$ is a template of size 3*3

$$W_L = 1/9 \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \tag{2}$$

Then the salient factor is calculated to determine which mode either selection or averaging mode to be used

$$M_j^{AB}(x,y)=2\sum_m \sum_n a_j^A(x+m,y+n)a_j^B(x+m,y+n)/E^A(x,y)+E^B(x,y) \tag{3}$$

Where $a_j^x(x,y)$; $x=A,B$ denotes the lowpass contourlet coefficients of the source image A or B.

Salience factor reflects the similarity of the lowpass subbands of the two source images. Then this value is compared to a predefined threshold T_L. If $M_j^{AB}(x,y)>T_L$, the source coefficient $a_j^A(x,y)$ and $a_j^B(x,y)$ are similar. On this condition use averaging mode and information is obtained from the contourlet coefficients of both the source image.

$$a_j^F(x,y)=\alpha_A.\, a_j^A(x,y)+ \alpha_B.\, a_j^B(x,y) \tag{4}$$

Where $a_j^F(x,y)$ is fused result at position (x,y). α_A and α_B are weights

$$\alpha_A = \begin{cases} \alpha_{min} \text{ for } E^A(x,y)< E^B(x,y) \\ \alpha_{max} \text{ for } E^A(x,y)>= E^B(x,y) \end{cases} \tag{5}$$

where $\alpha_B = 1- \alpha_A$ where $\alpha_{min} € (0,1)$ $\alpha_{min}+ \alpha_{max}=1$

For the condition $M_j^{AB}(x,y)<= T_L$, then use the selection mode as

$$a_j^F(x,y) = \begin{cases} a_j^A(x,y) \text{ for } E^A(x,y)>= E^B(x,y) \\ a_j^B(x,y) \text{ for } E^A(x,y)<E^B(x,y) \end{cases} \tag{6}$$

b) Highpass subband fusion: The selection of highpass coefficient depends on their absolute value without taking any consideration of lowpass subband [1].

The definition of contourlet contrast must conform to the relationship between low and high-pass coefficients. Suppose a k-direction Directional Filter Bank (DFB) is applied at the pyramidal level j of the LowPass (LP) then contourlet contrast can be defined as

$$S_{j,k}(x,y) = d_{j,k}(x,y) / \sum_m \sum_n a_j(x+m,y+n) \quad (7)$$

Where $d_{j,k}(x,y)$ is the highpass contourlet coefficients corresponding to sharp brightness changes and contours; $a_j(x,y),(m,n)\in W_Q$ is the corresponding parents coefficients in the coarser level.

For all highpass subbands b_J, $1<j<J-1$, it is represented as

$$SR_{j,k}(x,y) = \sum_m \sum_n W_H(m,n).\, S_{j,k}(x+m,y+n) \quad (8)$$

Where $(m;n)$ is the current coefficient, $W(m;n)$ defines a window of neighboring contourlet contrast centered around the current coefficients $d_{j,k}(x,y)$. The size of $W\,(m;n)$ is relatively small and must satisfy normalization ruled

$$\sum_m \sum_n W_H(m,n) = 1 \quad (9)$$

A weighted template based on city-block distance is used, which is

$$W_H = 1/16 \begin{matrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{matrix} \quad (10)$$

The region-based contourlet contrasts at the same position from the two source images are then compared with each other. Larger value of contourlet contrast means more high frequency information:

$$d^F_{j,k}(x,y) = \begin{cases} d^A_{j,k}(x,y) & for\ SR^A_{j,k}(x,y) >= SR^B_{j,k}(x,y) \\ d^B_{j,k}(x,y) & for\ SR^A_{j,k}(x,y) < SR^B_{j,k}(x,y) \end{cases} \quad (11)$$

c) Reconstruction of fusion image: This reconstruction work is inverse of cotourlet transform decomposition [1]:

$$\{b_1^F, b_2^F, \ldots.. b_{J-1}^F, a_J^F\} = f^1(x,y) \quad (12)$$

Where a_j^F fused lowpass subband at the coarsest scale j, $b_j^F, j=1,2\ldots J$ is the fused directive highpass subband set.

2.4 Quantitative Analysis on Fused Image

The quantitative measurement is done on the fused images using some objective quality measures [6]. It helps better in assessing the required information from the images. The following section explains the quantitative metrics used in the analysis of the proposed system.

1) Standard Deviation (SD): *The standard deviation gives the contrast information of an image [12,13]. The image with high contrast has high value of standard deviation and low for low contrast images. It is given as*

$$\sigma = \sqrt{1/N \sum_{i=1}^{N} (xi - x)^2} \quad (13)$$

Where X is defined as a summation

$$X = 1/N \sum_{i=1}^{N} xi = x_1 + x_2 + \ldots.. + x_N/N \quad (14)$$

2) Entropy (EN): Entropy directly reflects the amount of information in certain image [9,11]. If the values are larger better fusion result is obtained:

$$EN = -\sum_{i=0}^{L-1} P_F(i) log_2 P_F(i) \quad (15)$$

P_F is the normalized histogram of the fused image to be evaluated; L is the maximum gray level for a pixel in the image.

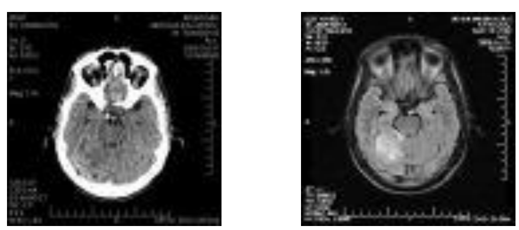
3) Power Signal to Noise Ratio (PSNR): This is defined as the ratio of the mean pixel value to the standard deviation of the pixel values [11].

PSNR = Mean pixel/Standard Deviation pixel (16)

3. Implementation Details

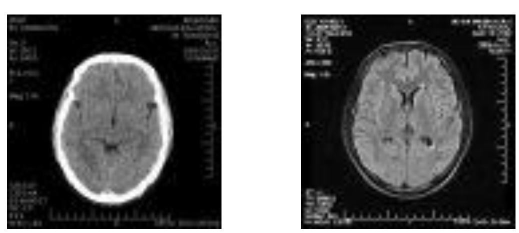
The steps given below describe the fusion of input images with this performance analysis.

Step 1: *Consider in*put images of CT and MRI (MR-T2) as a group. Size of all images has 256 * 256 pixels, with 256-level gray scale. Totally, eight groups of images are used for analysis. Some of the sample set of input images (Dataset-4 and Dataset-5) are shown in Figure 2 and Figure 3.



CT MRI (MR-T2)

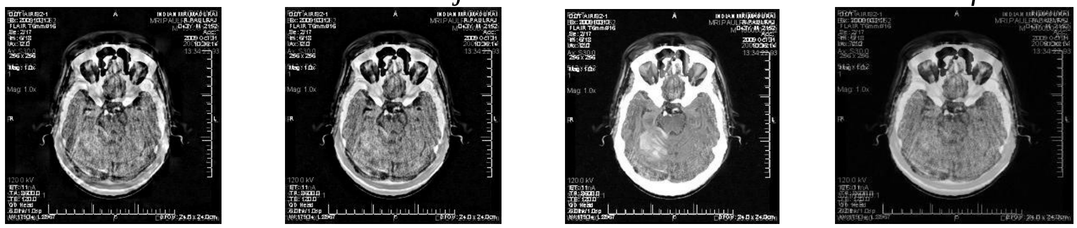
Figure 2 Original Multimodality Image Dataset 4



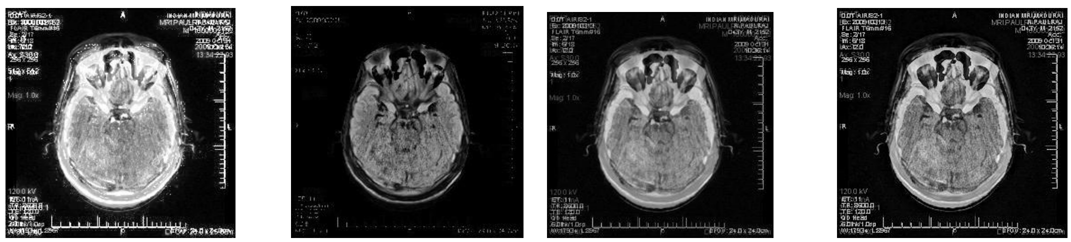
CT MRI (MR-T2)

Figure 3 Original Multimodality Image Dataset 5

Step 2: The given input images of each dataset are fused using various methods of Fusion tool and Contourlet Transform and samples are shown in Figure 4 and Figure 5.

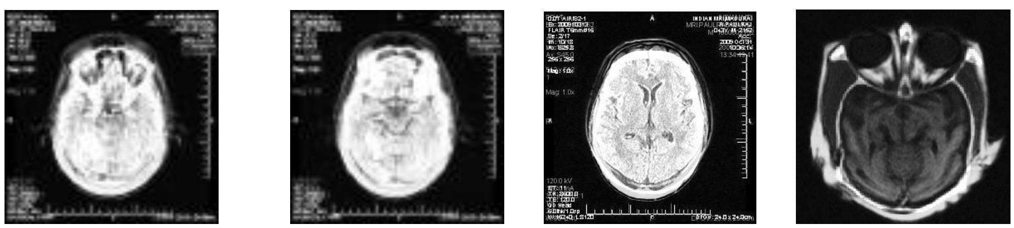


(1) DWT (2) SIDWT (3) Maximum (4) PCA



(5) ratio (6) Minimum (7) Average (8) Gradient

Figure 4 Fused Images of Dataset 4



Contourlet Transform

Figure 5 Fused Images of Dataset 4, Dataset 5, Dataset 6 and Dataset 7

Step 3: As discussed in section 2, the performance of fused images are analysed with quantitative metrics. Resultant of SD, EN and PSNR metrics is shown as table (I-III) and all metrics shown as graph in figure (Figure 6. to Figure 8).

Table-I: Standard Deviation Calculation

Methods	DataSet1	DataSet2	DataSet3	DataSet4	DataSet5	DataSet6	Dataset7
Average	0.3450	0.3664	0.3571	0.3619	0.3821	0.3682	0.3188
Contrast	0.1206	0.1175	0.1207	0.1296	0.1315	0.1304	0.0863
DWT	0.2300	0.2092	0.2105	0.2174	0.2270	0.2292	0.3593
FSD	0.3377	0.3218	0.3154	0.3169	0.3342	0.3250	0.4343
Gradient	0.3231	0.3071	0.3004	0.3045	0.3198	0.3128	0.4341
Laplacian	0.1826	0.2176	0.2135	0.2072	0.2229	0.2202	0.3294
Max	0.4289	0.3669	0.3933	0.3883	0.4051	0.4088	0.4630
Min	0.1159	0.1050	0.1071	0.1146	0.1165	0.1156	0.0835
Morpological	0.3454	0.3440	0.3400	0.3356	0.3555	0.3664	0.4539
PCA	0.3271	0.2676	0.2568	0.2709	0.2812	0.3124	0.5175

Ratio	0.4023	0.3796	0.391	0.3208	0.3491	0.3254	0.3748
Sidwt	0.2210	0.2013	0.1976	0.1998	0.2123	0.2160	0.3290
Contourlet	0.4146	0.3752	0.3929	0.3815	0.3947	0.3982	0.4605

Table-II: Entropy Calculation

Methods	DataSet 1	DataSet 2	DataSet 3	DataSet 4	DataSet 5	DataSet 6	Dataset7
Average	6.0757	6.2969	6.1837	6.2724	6.3294	6.1978	5.9228
Contrast	4.5800	4.3813	4.5272	4.8816	4.9463	4.8858	2.5225
DWT	5.9713	5.6734	5.7314	5.8858	5.9812	5.9581	6.1870
FSD	6.2367	6.1655	6.1249	6.1906	6.2702	6.1735	6.3469
Gradient	6.2116	6.1233	6.0723	6.1650	6.2439	6.1534	6.3317
Laplacian	5.5349	5.6839	5.6837	5.7609	5.8959	5.8204	6.2461
Max	6.3636	6.1056	6.2839	6.3097	6.3147	6.2845	6.7582
Min	4.1564	3.7796	3.7650	4.1283	4.2061	4.1216	2.0906
Morpological	6.1885	6.2203	6.1766	6.2946	6.3243	6.3312	6.5660
PCA	6.0341	5.8949	5.8869	6.0604	6.1032	6.0544	6.7142
Ratio	6.5230	6.2045	6.1214	6.3448	6.6903	6.5100	6.4979
Sidwt	5.8261	5.5488	5.5544	5.7028	5.8203	5.7742	6.0566
Contourlet	6.6934	6.4640	6.3263	6.4267	6.7367	6.6542	6.8371

Table-III: Power signal to noise ration calculation

Methods	DataSet1	DataSet2	DataSet3	DataSet4	DataSet5	DataSet6	Dataset7
Average	0.3450	0.3664	0.3571	0.3619	0.3821	0.3682	0.3188
Contrast	0.1206	0.1175	0.1207	0.1296	0.1315	0.1304	0.0863
DWT	0.2300	0.2092	0.2105	0.2174	0.2270	0.2292	0.3593
FSD	0.3377	0.3218	0.3154	0.3169	0.3342	0.3250	0.4343
Gradient	0.3231	0.3071	0.3004	0.3045	0.3198	0.3128	0.4341
Laplacian	0.1826	0.2176	0.2135	0.2072	0.2229	0.2202	0.3294
Max	0.4089	0.3669	0.3933	0.3783	0.4051	0.4088	0.4630
Min	0.1159	0.1050	0.1071	0.1146	0.1165	0.1156	0.0835
Morpological	0.3454	0.3440	0.3400	0.3356	0.3555	0.3664	0.4539
PCA	0.3271	0.2676	0.2568	0.2709	0.2812	0.3124	0.4175

Ratio	0.4023	0.3696	0.4010	0.3708	0.3891	0.3954	0.3748
Sidwt	0.2210	0.2013	0.1976	0.1998	0.2123	0.2160	0.3290
Contourlet	0.4146	0.3752	0.3929	0.3815	0.3947	0.3982	.4605

Step 4: In each graph, x axis values are specified with the dataset (1-7) and y axis shows the corresponding value derived from the specific metric for each method in the Fusion Tool and contourlet transform.

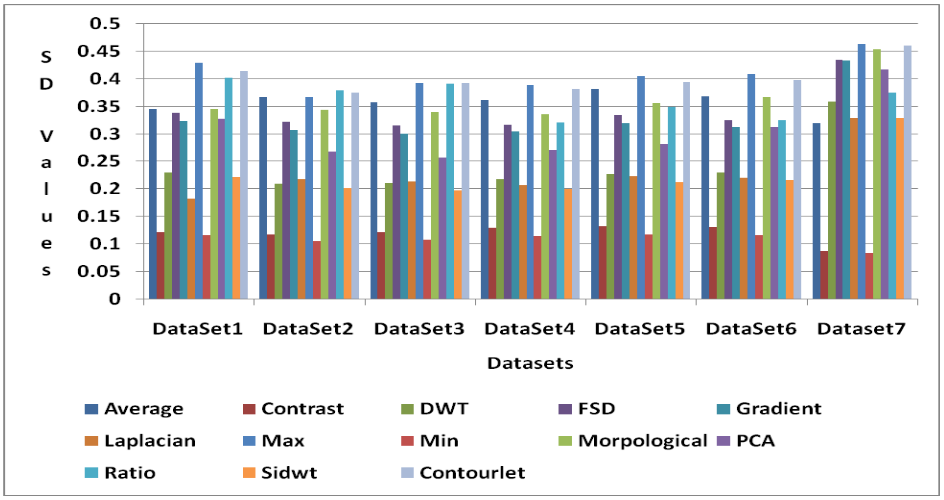


Figure 6 Graph-1 Standard Deviation Calculations.

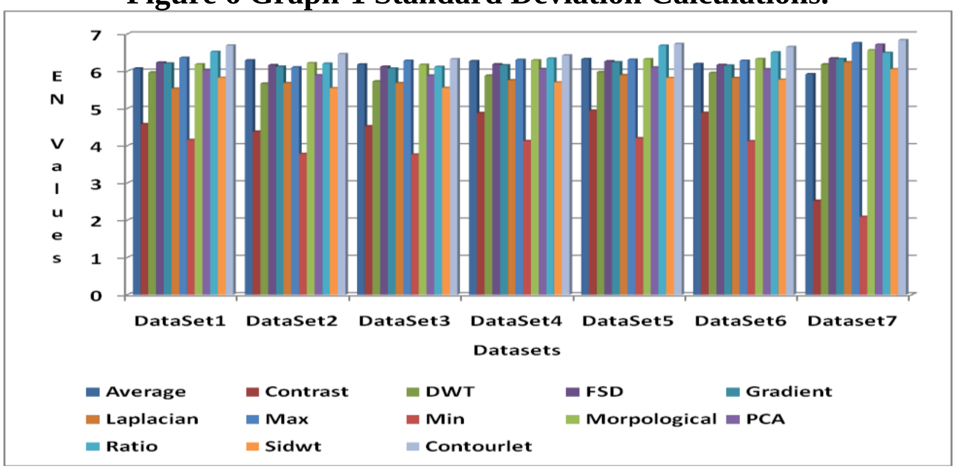


Figure 7. Graph-1I Entropy Calculation

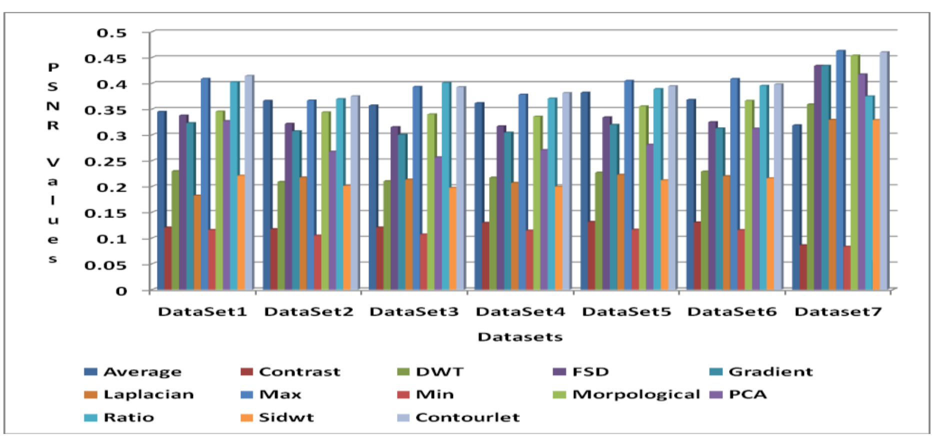


Figure 8. Graph-1II Power Signal to Noise Ratio Calculation.

Conclusion and Future Work

In this paper, the implementation of various quantitative metrics is done and using this, the performance of the fusion tool methods and contourlet transform method is evaluated. The results of each metric with all the methods are shown as table and graph. From the analysis the contourlet transform method, results with better performance with most of the metrics such as EN, PSNR. In future analysed results will be compared with the proposed techniques to identify the better fusion method for any type of modality images.

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