Image Fusion using Multi Resolution transforms with Human Visual System

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Abstract: The Quality of vision is a practical objective in the image processing. One of the applications of image processing procedures is Image Fusion. To get the subjective vision of a image by gathering the best data from source images of a similar scene/picture and spot them in a solitary void image is the Image Fusion process. A simple and versatile approaches are statistical measures, that are applicable in any kind of image/ signal processing techniques. In the first step, image is decomposed using Discrete Wavelet Transform (DWT). Mathematical computation of Smoothness is proposed in transform domain. This metric is used to select important information from multiple source images resulting to fused image. Further, Human Visual System (HVS) is also explored for fusion. Here all sub bands of DWT are multiplied with HVS weights. Highest response sub band is identified from various sub bands of multiple images using HVS. These sub bands are selected to get the fused image. Smoothness based fusion technique identifies the good texture information and leave the noise affected portions from the multiple source images. HVS based fusion technique identifies the visually important information from the multiple source images. The registered multi-focus and medical images are considered as source images. The experimental results shows that proposed fusion techniques are good in terms of popular fusion metrics.

Index Terms—Image Fusion, Discrete Wavelet Transform (DWT), Smoothness, Human Visual System (HVS)

1. INTRODUCTION

Square-block based image blend systems have a couple of limitations. The Fused-images consolidate obstructing antiquated rarities in the areas, where particular sensor information is basically novel. The Multi-Resolution change based image combination in the areas, conveys an inexorably trademark Fused-image, regardless, when the images to be merged are one of a kind. The image handling framework is being utilized to advance the visual nature of the pictures. Advanced image combination is one of the novel image preparing methods. Image handling utilizing block- based techniques [9] experience the ill effects of hindering antiques. A portion of the Multi-Resolution changes is Continuous Wavelet Transform (CWT), Discrete Wavelet Transforms (DWT), Dual-Tree Discrete Wavelet Transform (DTDWT), Curvelet Transforms (CVT), Contourlet Transforms (CT), Non-Sub Sampled Contourlet changes (NSCT), and Shearlet changes. Changes in the mix with Statistical estimates help to perceive basic data from the source pictures. Multiscale deteriorationbased combination methods are well known.

These methods incorporate the get-together of the source pictures reliant on a factor called the action/development level measure. The summary can be closed by picking the band coefficients of the source
pictures with higher development levels. The combined image is accomplished by performing Inverse multi-
scale change structures. DWT [1,11,12] is a Multi-Resolution change strategy used for image combination. An
efformous bit of the spatial space Image combination structures are assorted and time overwhelming and thusly,
are not suitable for continuous applications. In most of the interchanges, data and the pictures are packed, before
transmission, utilizing the JPEG/JPEG2000 code-stream design. The JPEG techniques experience the ill effects
of obstructing curios. Thus, the JPEG2000 system is considered in this work [2]. The JPEG2000 utilizes DWT.
There are numerous references to the JPEG2000. Those are the goal exactness, decision of lossless or lossy
pressure, adaptable record design, immense unique reach uphold, full help of straightforwardness, and reformist
transmission. The Smoothness measure is performed to perceive the huge endeavor powers of each band of
DWT. The Smoothness of the groups ought to be high to acquire fewer clamor groups. It is more material to
recognize the data which is liberated from high-recurrence commotion or Gaussian clamor in the picture.

The HVS [7] cover is helpful in recognizing the perceptual significant data. The best quality outcomes are seen
by receiving the HVS [4] model for picture handling. HVS has involved credits like affectability, splendor
variation level, and surface movement. Shuo et al. [15] proposed combination calculations dependent on Multi-
Resolution change and a near report is performed by Krishnamoorthy and Soman [5] on picture combination
calculations. In past, the HVS loads of DWT are resolved to utilize the Contrast Sensitivity Function (CSF) veil
for watermarking applications [6, 7,10,16]. The greatest degree of neighborhood energy-based Image
combination in the DWT area is investigated by Hui Li et al. [18].

In the DWT space, the Maximum-Absolute (Max-Abs) estimation of the coordinating band coefficients, with
HVS loads [13, 14] at every disintegration level, is chosen as the action level. In past investigations, DWT is
utilized in numerous applications, for example, pressure, watermarking [3], and picture combination. DWT with
the greatest determination rule and DWT with normal-based picture combinations are famous [6, 9]. These
methodologies are very little ideal to distinguish outwardly significant data of the source pictures. In this work,
DWT with Smoothness and DWT with HVS approaches are proposed to recognize the perceptual significant
sub-groups from the source pictures for picture combination.

The original copy is coordinated in the accompanying mode. In area 2, a short writing survey about DWT is
given. In 3 segment a concise depiction given about the Smoothness measures in the wavelet is presented. The
use of HVS in DWT is talked about in 4 areas. The Image fusion calculation in DWT utilizing Smoothness
measures is given in area 5. The image fusion calculation utilizing HVS loads for deteriorated groups in DWT is
clarified in 6 segments. Usage and exploratory outcomes are given in 7 areas. The end to this original copy is
given in 8 areas.

2. DISCRETE WAVELET TRANSFORM

In DWT [8,11,12], an image can be created by surpassing it through an investigation of filter bank followed by a
destruction procedure. This filter bank investigation contains a low-pass and a high-pass filter at every decay
stage and is regularly utilized in Image processing. At the point when an Image surpasses through these filters,
they split into two groups. The low-pass filter, which keeps up a correspondence to an averaging capacity, pull
out the coarse data of the image. The high-pass filter, which keeps up a correspondence to a differencing
capacity, pull out the point by point information of the image / picture. The yield of the separating capacities is
then decimated by two. Some of the filters used in DWT for signal processing is shown in Figure 1.

Because of the surprising multifaceted nature of HVS and the relationship in the visual passageway, the
computational showing of HVS honestly from its physiology is absurd[17]. The two pictures to mix, similarly as
their connected weight maps, are discussed to propel the trade over of edges and concealing distinction to the
assent picture [8]. To avoid that the sharp weight map progresses make old rarities in the low-repeat sections of
the remake picture, we moreover embrace a multi-scale combination methodology. The Human Visual System
(HVS) sees inquiries in a couple of taking care layers which are continuous best quality outcomes are seen by
embracing the HVS in the picture preparation. The HVS involves affectability, splendor transformation, and
surface movement. Shutaota et al.[15] proposed the combination calculations with Multi-Resolution changes. A
similar report is performed by Sivasubramani and Soman [5] on picture combination calculations. In the
majority of the writing, the HVS loads of DWT are dictated by the CSF cover [7, 14] for watermarking
application. The most extreme degree of neighborhood energy-based picture combination in the DWT area is
investigated by Humin Lu et al.[18]. Bing et al[19] endeavor to give a diagram of multimodal clinical picture
combination techniques, placing accentuation on the latest advances in the area dependent on (1) the present
combination strategies, remembering based for profound learning, (2) imaging modalities of clinical picture
combination, and (3) execution examination of clinical picture combination on primary informational index. The visual data can be accomplished with the assistance of HVS weights. The transform domain procedures are computationally mind-boggling and additionally tedious. When all is said done, communication of information is to be compacted before transmission. The coded pictures are in the JPEG 2000 organization. The primary applications with image fusion are in clinical determination with sets of CT and MRI, PET (Positron Emission Tomography) and MRI, combat zone imaging, remote detecting, vision in mechanical autonomy, and satellite imaging.

Figure 1. Display of Haar, D4 (Daubechies), S8 Symlets, and C3 Coiflets Wavelets

3. SMOOTHNESS MEASURE IN WAVELET TRANSFORM DOMAIN

In Wavelet domain, the Smoothness is calculated for each band of frequencies. The relative Smoothness value approaches zero for steady intensities in a region and is one for regions having a large expedition in the intensity values. The procedures of Smoothness calculations are given below.

The approximation band in DWT is given in equation below is

\[
\Psi_{j_0,u,v}(x,y) = \frac{1}{\sqrt{MM}} \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} f(x,y) \phi_{j_0,u,v}(x,y)
\]

and the Smoothness of each sub-block is calculated in spatial domain and is shown as below

\[
S_{j=0}(u,v) = 1 - \frac{1}{1 + V_{u,v}}
\]

where \(V_{u,v}\) is the variance of the approximation band. \(S_{j=0}(u,v)\) is the Smoothness of approximation band.

The Smoothness (transform domain) of detailed bands given in equation is

\[
\Psi_{j,u,v}(x,y) = \frac{1}{\sqrt{MM}} \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} g(x,y) \psi_{j,u,v}(x,y)
\]

The Smoothness can be calculated using equation (2) is given below

\[
S_{j=2,3,4}(u,v) = \sum_{a,v} \left| \Psi_{j,u,v}(x,y) \right|
\]

where \(S_{j=2,3,4}(u,v)\) are the Smoothness of the vertical, horizontal and detailed bands.

The Smoothness of the image in DWT is calculated using the equation (1) and equation (2). The \(C^1\) band is an approximation band, having an average of all pixels in the image. The detailed bands contain the transform
coefficients. The Smoothness measures of approximation band are calculated using the equation (1). \( \theta = \{1, 2, 3, 4\} \). For \( \theta = 1 \), is the approximation band and \( \theta = \{2, 3, 4\} \) represents the vertical, horizontal and detailed bands.

4. HUMAN VISUAL SYSTEM IN WAVELET TRANSFORM DOMAIN

Human Visual System (HVS) is a mathematical model expanded for human vision that consider how sensitive to contrast, colour and brightness. The CSF explores the sensitivity to spatial frequencies of luminance images. The luminance contrast sensitivity function is shown in Figure 2. Mannos and Sakrison [20] derived a mathematical model of CSF for gray (or luminance) images.

\[
CSF(F) = 2.6(0.192 + 0.114F) e^{-(0.114F)^{0.5}}
\]

where \( F \) (in cycles/degree) is the spatial frequency is given as \( F = \sqrt{F_x^2 + F_y^2} \). \( F_x \) is the spatial frequency in horizontal direction. \( F_y \) is the spatial frequency in vertical direction.

![Figure 2. A model graph of luminance Contrast Sensitivity Function](image)

5. IMAGE FUSION ALGORITHM USING SMOOTHNESS MEASURE

The various steps involved in the proposed fusion algorithm using Smoothness measures.

![Figure 3. Block diagram of fusion approach using Smoothness in DWT domain](image)

![Figure 4. Fusion Process](image)
The process of the image fusion in DWT domain using Smoothness measures are explained in flow chart given in Figure 3 and 4.

The steps involved in the proposed fusion algorithm using Smoothness are given below:

1. Considering two or more source images for collecting information to obtain a fused image.
2. With the application of DWT, all the source images are transformed into wavelet domain.
3. Evaluate consequent Smoothness of the bands.
4. The Smoothness of approximation band is calculated using equation (1). Because the spatial components are contained in the approximation band.
5. The Smoothness in remaining detail bands are calculated using equation (2). The Smoothness of all sub-band coefficients are added using equations (3).

$$ S_Z = \sum S_Z (u, v) $$  (3)

6. The selection of the suitable sub-band depends on the activity level:

$$ A_F (u, v) = \begin{cases} \psi_{1R} & S_Z > S_{2Z} \\ \psi_{2R} & \text{otherwise} \end{cases} $$  (4)

The Smoothness of the sub-bands are compared, and the highest smoothened sub-band is selected from the source images with the help of equation (4). The flow of the fusion process is shown in Figure 5.
7. By concatenating the selected bands in a sequence, the fused image is formed.
8. Apply the inverse DWT to obtain the resultant Fused image.

6. IMAGE FUSION ALGORITHM USING HVS

The all-purpose block diagram for image fusion is shown in Figure 3. In this experimentation only two source images are considered. The multi-focused source images are prepared by using Gaussian low pass filter with $4 \times 4$ size and the standard deviation is 6. Each source image is transformed using the 5-level of DWT decompositions. The reconstructed image is very much disturbed due to blocking artifacts, when the square block size is considered less than 64 x 64 sizes.

6.1. Design of weights based on HVS

In order to create the DWT CSF mask, the numbers of decompositions are to be performed on the CSF curve. Andrew [6] has discussed about 5-level Bi orthogonal 9/7 wavelet decomposition of the CSF curve. In the decomposition process the subspaces are given as $W_5, ..., W_1, V_1$. The peak of the $W_5$ is denoted with $p_5$, the peak of the $W_4$ as $p_4$ and so on. Also the $V_5$ subspace is denoted with $q_5$. The peak subspace of $V_4$ denoted as $q_4$, peak of $V_3$ as $q_3$, peak of $V_2$ as $q_2$ and peak of $V_1$ subspace as $q_1$. For the first level of decomposition the weight of the diagonal band ($D_1$) is given as $p_5$. The sub- band weights for $H_1$ and $V_1$ are given as square root of $q_5$ and $p_5$. For the second level of decomposition the weight for $D_2$ is $p_4$ and the sub- bands $H_2$ and $V_2$ are given as square root of $q_4$ and $p_4$. Similarly, the weights are determined for all decompositions remained. At the final, all the peaks are normalized and the lowest peak will be equal to one. Likewise, this method constitutes 11 unique weights in the mask.

The mathematical model developed for HVS is developed by considering the vision sensitivity to noise variations, local-brightness, and local-texture activities in the approximation and detailed bands. The weight function to determine the HVS is determined by the combination of three terms in given equation (5):

$$S^\theta_{1}(u,v) = \left( \Theta(l,\theta) \cdot \Lambda(l,u,v) \cdot E(l,u,v)^{0.2} \right) / 2$$

where, $l$ represents the level of decomposition, $\Theta(l,\theta)$ represents the noise changes in sensitivity measure, $\Lambda(l,u,v)$ represents the brightness, measure and $E(l,u,v)$ represents the texture activity. $\Theta(l,i)$ represents the sensitivity of the human vision to noise changes and is calculated using equation (6):

$$\Theta(l,\theta) = \begin{cases} \sqrt{2} \text{ if } \theta = 1 \\ 1.00 \text{ if } l = 1 \\ 0.32 \text{ if } l = 2 \\ 0.16 \text{ if } l = 3 \\ 1 \text { otherwise} \end{cases}$$

The brightness or darkness is calculated using equation (7)

$$\Lambda(l,u,v) = 1 + L^1(l,u,v)$$

where

$$L^1(l,u,v) = \begin{cases} 1 - L(l,u,v), \text{ if } L(l,u,v) < 0.5 \\ L(l,u,v), \text{ otherwise} \end{cases}$$

$$L(l,u,v) = \frac{1}{256} \sum_{r=0}^{3} (1 + \frac{u}{2^{r-1}}) \cdot \left[ 1 + \frac{v}{2^{r-1}} \right]$$

$E(l,u,v)$ represents the sensitivity of the human eye to the texture activity in the neighborhood of a pixel

$$E(l,u,v) = \sum_{r=0}^{3} \frac{1}{16} \sum_{\theta=0}^{3} \sum_{u=0}^{2^r} \sum_{v=0}^{2^r} \left[ I^\theta_r(y+\frac{u}{2^r}, x+\frac{v}{2^r}) \right]^2 \cdot \text{Var} \left[ \frac{3}{3^r} \left( 1 + y + \frac{u}{2^{r-1}}, 1 + x + \frac{j}{3^{r-1}} \right) \right]$$

$x = 0.1 \quad y = 0.1$
Using the equation (5), the HVS weights are calculated. The eleven unique weights for DWT CSF are given in Table 1. The proposed fusion algorithm DWT with HVS process is expressed using a flow chart which is given in Figure 6. The selection process explained in Figure 7.

| Sub-band | Weight | Sub-band | Weight |
|----------|--------|----------|--------|
| D₁ = V₁  | 1.00   | D₄       | 3.48   |
| H₁ = V₁  | 2.33   | H₄ = V₄  | 3.55   |
| D₂       | 3.75   | D₅       | 3.21   |
| H₂ = V₂  | 4.74   | H₅ = V₅  | 3.48   |
| D₃       | 7.20   | C₅       | 3.78   |
| H₃ = V₃  | 5.30   | ---      |        |

In the Fusion Process, each sub block is transformed into sub-bands up to the fifth level of decomposition of DWT. Similarly the CSF curve is also decomposed up to the fifth level and also calculated the weights of each sub-band. Each and every sub-band is multiplied with consequent weights of CSF. The total sub-band weight is determined by summing up of all sub-bands. An assessment is performed between the weights of sub-bands, and select corresponding sub-bands from source images. Similarly, all the sub-bands are selected and fused in an empty image.

6.2. Algorithm for Proposed method
The general image fusion procedure, applying the 2D-DWT in each source image, is explained below. The HVS weights of all sub-bands of DWT domain are calculated. The result of for every band is calculated using HVS weights of the consequent band. The highest resultant bands are opted for Image Fusion.

\[ \Psi(u,v) = \left[ \Psi_{0}(j_0, u, v) + \Psi_{j}(j, u, v) \right] \ast S_{j}(u,v) \]  

(8)

The net weight of each sub-band is calculated by pooling up all the weighted signals.

\[ R_j = \sum \sum \Psi(u,v) \]  

(9)

The supreme value of the activity level is given in equation (10).
\[ R_t = \left| R_t \right| \quad (10) \]

The subsequent step in Image Fusion is to select the right sub-band by using activity level:

\[ A_F (u, v) = \begin{cases} \psi_{1R} & R_{1t} > R_{2t} \\ \psi_{2R} & \text{otherwise} \end{cases} \quad (11) \]

where \( \psi_{1R} \) is the result of the first image sub-band and \( \psi_{2R} \) is the response of the second image sub-band. The comparison is performed between the sub-bands, and the highest response sub-band is chosen. Similarly, all the sub-band coefficients are chosen to obtain a Fused Image. The various steps involved in the proposed fusion algorithm.

The steps involved in the proposed fusion algorithm are given below:
1. Considering at least two source pictures for gathering data for combination.
2. Apply DWT on each source image.
3. Select the HVS loads.
4. Increasing every single sub-band coefficient with the particular HVS loads as given in condition (8).
5. The reactions of each sub-band are looked at, and the best sub-band is chosen for image combination utilizing condition (11).
6. Inverse DWT is applied to the chose sub-groups to get the Fused Image. The flow of the method is shown in Figure 8.

**Figure 8.** Flow chart representation of the proposed (DWT+HVS) algorithm.

### 7. IMPLEMENTATIONS AND EXPERIMENTAL RESULTS

The basic wavelet family is Haar. In order to compare the results of the proposed algorithm with the existing algorithms using the Haar filter using the performance measures such as MI, \( Q^{10/7} \), FSIM, and NCC. The results of the programs executed using multi-focus images are shown in Table 2. The best results are given in
bold. Similarly, the results of proposed algorithm (DWT+HVS) are executed using various filter of wavelet transforms are given in Table 3. In Table 4, the results of proposed algorithms using multi-sensor images (medical) are given. In Table 5, the comparisons of results with existing algorithms [15] for Pepsi image are given. In Table 6, the comparisons of results with existing algorithms [15] for medical images are given.

### Table 2. Comparisons of DWT+HVS, DWT+Smoothness, DWT

| Multi-focus image | Filter | PSNR  | MI   | \(Q_{U/D}\) | FSIM  | NCC   |
|-------------------|--------|-------|------|-------------|-------|-------|
| DWT+HVS           | Clock  | Haar  | 92.0829 | 4.4910     | 0.9166 | 0.9997 | 0.9992 |
| DWT+Smoothness    | Clock  | Haar  | 91.7003 | 4.3589     | 0.8887 | 0.9996 | 0.9991 |
| DWT [15]          |        | Haar  | 69.5322 | 1.9900     | 0.4648 | 0.9840 | 0.9429 |
| DWT+HVS           | Disk   | Haar  | 86.3939 | 3.9216     | 0.8958 | 0.9995 | 0.9978 |
| DWT+Smoothness    | Disk   | Haar  | 86.3407 | 3.7707     | 0.8834 | 0.9995 | 0.9977 |
| DWT [15]          |        | Haar  | 66.4404 | 1.8400     | 0.5239 | 0.9908 | 0.9468 |
| DWT+HVS           | Pepsi  | Haar  | 85.9132 | 4.0099     | 0.8871 | 0.9996 | 0.9974 |
| DWT+Smoothness    | Pepsi  | Haar  | 88.7772 | 3.9009     | 0.8947 | 0.9997 | 0.9986 |
| DWT [15]          |        | Haar  | 68.3096 | 1.8042     | 0.4899 | 0.9742 | 0.9430 |
| DWT+HVS           | Books  | Haar  | 82.8714 | 3.7809     | 0.8555 | 0.9995 | 0.9970 |
| DWT [15]          |        | Haar  | 66.4733 | 1.7378     | 0.5074 | 0.9897 | 0.9435 |
| DWT+HVS           | Toy    | Haar  | 83.3418 | 3.4135     | 0.8691 | 0.9996 | 0.9960 |
| DWT+Smoothness    | Toy    | Haar  | 84.5682 | 3.0883     | 0.8534 | 0.9995 | 0.9969 |
| DWT [15]          |        | Haar  | 65.9770 | 1.7508     | 0.4834 | 0.9937 | 0.9472 |
| DWT+HVS           | Paper  | Haar  | 75.8660 | 3.1565     | 0.8497 | 0.9989 | 0.9688 |
| DWT+Smoothness    | Paper  | Haar  | 77.6985 | 2.7444     | 0.8259 | 0.9990 | 0.9796 |
| DWT [15]          |        | Haar  | 66.6294 | 1.5828     | 0.5498 | 0.9919 | 0.9415 |
| DWT+HVS           | Lena   | Haar  | 81.3947 | 3.7678     | 0.8583 | 0.9994 | 0.9933 |
| DWT+Smoothness    | Lena   | Haar  | 86.3687 | 3.8884     | 0.8880 | 0.9997 | 0.9979 |
| DWT [15]          |        | Haar  | 65.6061 | 1.7972     | 0.5147 | 0.9905 | 0.9511 |
| DWT+HVS           | Cameraman | Haar  | 83.0978 | 3.7701 | 0.8440 | 0.9993 | 0.9973 |
| DWT+Smoothness    | Cameraman | Haar  | 80.5458 | 3.1482 | 0.8301 | 0.9993 | 0.9952 |
| DWT [15]          |        | Haar  | 66.0120 | 1.9403 | 0.5563 | 0.9867 | 0.9436 |

The performance of proposed approach DWT+HVS is superior in all fusion metrics (stated) for Clock, Books, and Lena images.

**Figure 9.** Clock image. Top left corner is the original image, Top right corner is right blurred image, bottom left corner is left blurred image, and bottom right corner is the fused image (DWT + HVS)
**Figure 10.** Pepsi image. Top left corner is the original image, Top right corner is right blurred image, bottom left corner is left blurred image, and bottom right corner is the fused image (DWT + HVS).

**Figure 11.** Cameraman image. Top left corner is the original image, Top right corner is right blurred image, bottom left corner is left blurred image, and bottom right corner is the fused image (DWT + HVS).

| Source images | Filter | PSNR | MI   | $Q^{max}$ | FSIM     | NCC   |
|---------------|--------|------|------|-----------|----------|-------|
| Clock(Multi-focus) | Haar   | 92.0829 | 4.4910 | 0.9166    | 0.9997   | 0.9992|
|                | Db2    | 89.4750 | 4.3720 | 0.9106    | 0.9923   | 0.9985|
|                | Db5    | 89.4790 | 4.3720 | 0.9106    | 0.9924   | 0.9985|
|                | Sym2   | 89.4790 | 4.3720 | 0.9106    | 0.9923   | 0.9985|
Results of DWT+HVS with different filters are executed on a multi-focus images are shown in Figure 9, 10, and 11. The summary of performance evaluation using different filters with different orders in DWT+HVS approach are given in Table 3.

| Source images | Filter  | PSNR  | MI    | $Q^{f1/f2}$ | FSIM  | NCC   |
|---------------|---------|-------|-------|-------------|-------|-------|
|               | Sym3    | 89.4790 | 4.3720 | 0.9106      | 0.9924 | 0.9985 |
|               | coif1   | 92.0827 | 4.5221 | 0.9165      | 0.9921 | 0.9992 |
|               | Bior1.3 | 92.0827 | 4.5221 | 0.9165      | 0.9921 | 0.9992 |
|               | Bior3.7 | 89.4750 | 4.3720 | 0.9106      | 0.9923 | 0.9995 |
|               | rbio1.1 | 92.0827 | 4.5221 | 0.9165      | 0.9921 | 0.9992 |
|               | rbio2.2 | 92.0827 | 4.5221 | 0.9165      | 0.9921 | 0.9992 |

**Figure 12.** Graphical representation of comparison among approaches in MI

**Figure 13.** Graphical representation of comparison among approaches in $Q^{f1/f2}$
Figure 14. Graphical representation of comparison among approaches in FSIM

In the graphical representation Figure 12, the results for Clock is clearly visible the difference between proposed to existing method. The MI is greater in 2 bits for proposed method. Very fewer differences are observed in $Q_{fb/F}$ and FSIM are observed in Figure 13 and Figure 14 respectively.

Table 4. Performance results of proposed approaches to medical images (DWT + HVS) using rbio2.2 filter

| Source images | Fusion rule | Filter | $Q_{fb/F}$ |
|---------------|-------------|--------|------------|
| CT, MRI       | DWT [15]    | rbio2.2| 0.1495     |
|               | DWT + Smoothness | rbio2.2 | 0.3157     |
|               | DWT + HVS   | rbio2.2| **0.6660** |

From the Table 4, the proposed algorithm DWT+HVS is superior in all measures. Blocking artifacts are less compared with DWT+HVS. The results of medical imaging is given in Figure 15. The graphical representation of performance metric is shown in Figure 16.

Figure 15. Medical images, Top left corner is original image, Top right corner is CT image, bottom left corner
is MRI image, and bottom right corner is the fused image (DWT + HVS)

Figure 16. Graphical representations among the approaches for medical images (MRI, CT)

The comparison of proposed algorithms with Shutao et al [15] is given in Table 5. It is clearly visible the superiority of the proposed algorithms for Multi-focus images. Best results are tabulated in Table 6.

| Fusion Rule | Filter  | Level | $Q^{\beta/2}/F$ |
|-------------|---------|-------|---------------|
| DWT         | Haar    | 5     | 0.7259        |
| SWT         | Sym2    | 3     | 0.7544        |
| DWT [15]    | q-6 (5-3) | 4     | 0.7344        |
| CVT         | Pyr (5-3), Ori (9-7) | 4     | 0.7460        |
| NSCT        | Pyrexe (7-9) | 4     | 0.7589        |
| DWT + Smoothness | rbio2.2 | 5     | 0.8887        |
| DWT + HVS   | Haar    | 5     | 0.9166        |

Table 6. The performance comparison for medical images

| Fusion Rule | Filter  | Level | $Q^{\beta/2}/F$ |
|-------------|---------|-------|---------------|
| DWT [15]    | Db1     | 3     | 0.1890        |
| DWT [15]    | rbio2.2 | 5     | 0.1495        |
| SWT [15]    | Coifl   | 4     | 0.5970        |
| DWT [15]    | q-6 (5-3) | 3     | 0.5573        |
| CVT [15]    | Pyrexe  | 3     | 0.6386        |
| NSCT [15]   | Pyrexe  | 3     | 0.3157        |
| DWT + Smoothness | rbio2.2 | 5     | 0.6660        |

From Table 6, it is clearly observed that the superiority of proposed algorithms over the existing algorithms on medical images.

8. CONCLUSION

The proposed approaches are based on smoothness measure and HVS method in Multi Resolution transform domains respectively. To eliminate the blocking artifacts we considered a full frame transform like DWT. In DWT domain, the Smoothness based measure gives better results when source images are affected by noise. We
observed that the MI is comparatively high due to less scaling and ringing artifacts. While in comparison with various wavelet families rbio2.2 wavelets give best results for MI, $Q^{f_1f_2}_F$, and FSIM. HVS based processing preserves the required information as per the human perception. In general, HVS based method produces better results when compared with the existing methods. Overall improvement of 96.757 % in MI is observed with HVS based method for multi-focus image fusion. For medical image fusion, the overall improvement of 98.146 % in MI is observed with HVS based method. For instance, medical images (CT, MRI)Objective Score $Q^{f_1f_2}_F$ of fused medical image is 0.6660 and 0.3157 for DWT+HVS and DWT+Smoothness methods respectively. The time to implement DWT + HVS (Haar) approach is 0.9708544 seconds. Though the other proposed approach, DWT + Smoothness(Haar) has the elapsed time in seconds is 0.621165 seconds. DWT[15] (Haar) elapsed time 0.327612 seconds. The fused image quality is visually good for medical images using HVS model than the other transform based fusion techniques.

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