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Perceptual Image Fusion of CT and MR Images Using Wavelets

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Abstract: **---- This image fusion is that to employ explicit luminance and to contrast masking models. In this paper, the wavelet transform is used along with Dual-Tree Complex. By this Dual-Tree Complex, Wavelet Transform of each input image will be divided and will be diagnosed carefully. From this DTC the coefficients are retained and the retained information would be in the most effective way. For this image fusion, Discrete Wavelet Transform is used. In this paper, the complexity of finding out the disease from the MR and CT images will be simplified.**

***Key Words*: DT-CWT, DCT, DWT, Image Fusion.**

I. INTRODUCTION

The Effective fusion of two or more sources can provide benefits for visualization and also in medical surveillance and remote sensing. The output of the fusion process should employ perceptual models of Human Visual Systems (HVS).

The perceptive information from the two sources and should form a single more informative image. For exploiting multi-scale disturbances wavelets are used. The main perceptual things are:

1. Luminance Masking and
2. Variation of contrast perception.

Previously fusion can be done by the DCT or DWT. Now at present Dual-Tree Complex Wavelet Transform (DWT).Image fusion consists of pixel methods to combine two images. Wavelet transform in Particular provide a flexible multi-scale fusion, which is one of the technique in multi-scale transform to provide good fusion.

II. DWT

Two registered sources as inputs a0 and a1, the wavelet transform and a fusion rule ϴ, and then will combine co-located coefficients with in the transform domain.
$F= \omega-1 (\Theta (w(a0),w(a1))$.

Dual-Tree Complex Wavelet Transform (DT-CWT):

Discrete Wavelet Transform is associated to shift variance produces sub-optimal performance. This is solved by Shift Invariant DWT (SI-DWT).But it will remove the down sampling at each stage of the decomposition. So it is Shift variant.

The Dual-Tree Complex Wavelet Transform provides a significantly more compact transform domain representation not only achieves near Shift invariance but also provides directionality. This discrimination of results of DCT by taking the orientation of ±15, ±45, ±75.The DT-CWT offers several advantages for image fusion over other transforms.

Perceptually Based Image Fusion:

To integrate perceptual criteria into image fusion application, this fusion is employed to it. It will process the fusion with Laplacian Pyramid Decomposition using fusion rules.

It also integrates a localized version of "visibility metric" into fusion process. Visibility metric is simply a weighted a local variance and doesn't depend on luminance and contrast making. The "total variation" fusion approach uses a global luminance adaption function.

Perceptual models for image fusion:

The perceptual of contrast relevant to image fusion has been found to be dependent on a range of masking effects.

The main masking effects of this fusion are:

1. Luminance Masking: The dependence of contrast perception on local luminance.

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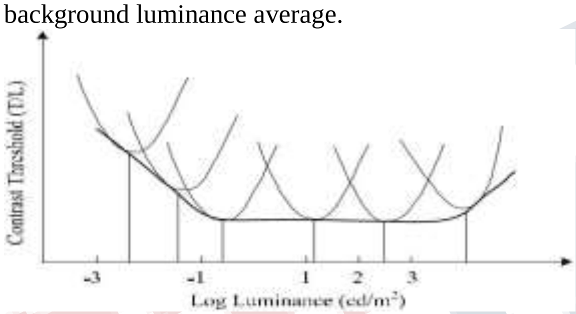
2. Contrast Masking: It also depends on orientation of local content.
3. Frequency Masking: The contrast Sensitivity Function (CSF) gives a measure of the perceptual importance of spatial frequencies.
These models are used to predict the behavior of HVS which depends on masking effects.

Luminance Masking/Adaptation:
It is for the perception contrast of luminance content by the Human Visual System (HVS) and also global background luminance levels. Luminance adaption has been conventionally representing the power law variants.
The weber-Fechner law states that the ratio of the JND threshold 'T' to the background luminance is constant over a range of 'L' Ratio (T/L) is for high and low background luminance values to take into account, the HVS will decrease JND threshold vary as a "quasi-parabola" or U-shaped curve for representing global background luminance average.



Local and global luminance JND threshold models

Parabola shaped curves are modulated by Weber Fechner global luminance masking effect.
1. Luminance masking model definitions: Proposed to define the noticeable differences and vibrations in the background luminance.
2. Calculation of local luminance: for DCT, DC transform block values will be taken and for DWT co-located coefficients of low sub band will be taken.

III.CONTRAST MASKING

Visibility of an image component varies in the presence of other image components.
It is basically the variation of the JND threshold of a target signal as a function of the intensity of a masking signal.
Measure of contrast masking 'a_c' can be modelled using DT-CWT.
$a_c\ (\lambda, \theta, i, j) = a_{c\_int\,r\,a}(\lambda, \theta, i, j)\, a_{c\_inter}(\lambda, \theta, i, j),$

a_c _intra (λ, θ ,i, j) is the contrast masking effect due to the coefficients with in the same sub band on the target coefficient.
Variation masking with orientation and taken into account of large number of more closely related coefficients.

1) Intra-band Contrast Masking:

Masking has the largest effect when the target and masker have the same frequency and orientation.
Intra-band contrast masking has the largest effect than the Inter-band masking.
Intra-band contrast masking for coefficient $v(_{\lambda,\theta,i,j)}, _{(\lambda,\theta)}$) is constant within the same sub band.

2) Inter-band Contrast Masking:

This can give conservation and tractable model that can be more supportive with a wider spatial orientation and frequency spread of masking signal. It defines for the symbols of $v_{\lambda,,\theta,i,j.}$

Effect of a contrast masking is observed only up to a relative frequency range of two octane. Orientation weights indicate the masking effect of an oriented

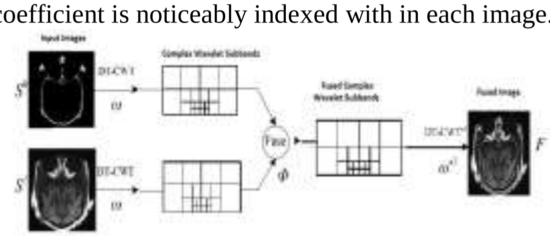
3) Contrast Sensitivity:

For these measures JND gave a spatial frequency more effectively. This is done with DWT because it increases in the spatial frequencies.

Perceptually Based Fusion Rules:

4) DT-CWT Coefficient Fusion:

As shown in below figure both the coefficients of two images are combined to form the fused image. This wavelet coefficient fusion rule has simplest form called maximum rule. Maximum fusion of its variance makes the perceptual importance of a coefficient α to magnitude. The measure of perceptual important coefficient is noticeably indexed with in each image.



Fusion Process

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Perceptually fused coefficients:

The adjusted coefficient of an each image will be the perceptual coefficients ever though they are adjusted the coefficients magnitude are relative to

$$v^3 = \begin{cases} V0_{\rho}\dfrac{t^{l}_{JND}}{JND} & NI^0 > NI^1, \\ V1_{l}\dfrac{t^{\rho}_{JND}}{JND} & \text{otherwise}, \end{cases}$$

Then by the maximum fused method the fusion process will done to the image and final fused image is obtained having coefficients of original image with extra clean information.
Visualization will give the intermediate vision of the input images with high luminance and high correlative value.

Algorithm:

Perceptual Fusion Algorithm

a) Give two input images s0 and s1.
b) Apply DT-CWT to s0 and s1.
c) Apply Max-Coefficient Fusion.
d) Apply initial fused DT-CWT transform
1) Apply Luminance Masking.
2) Apply Intra-band Contrast Masking.
3) Apply Inter-band Contrast Masking.
4) Combine Intra-Band and Inter-band Contrast Masking.

5) Applying JND Threshold to intra-band and inter-band.
6) Applying Noticeability Index of each Coefficient with in each image.
e) Apply Inverse DT-CWT.
f) *Output.*

IV. RESULTS

1) Artificial images

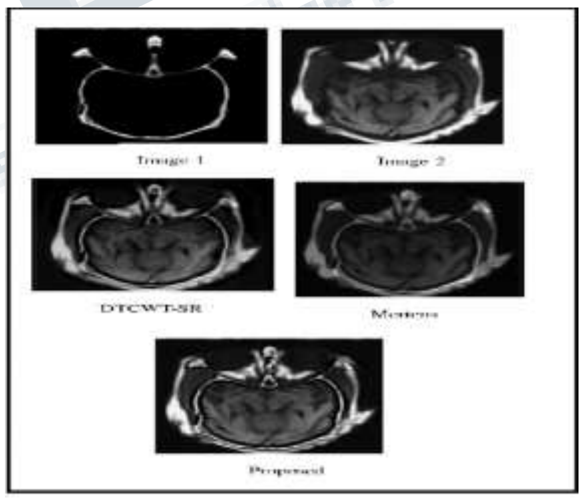
The effect of texture based contrast masking we have created two pairs of artificial images to fuse. Each column contains a distinct artificial image pair associated with their fusion results. The input image pairs comprise a texture of varying intensity and a discontinuity. The top left image shows the texture with gradually increasing contrast in vertical stripes in the image. Then the image should intended to isotropic intra-band masking.

3. Real Image

There are three fusion methods for real images
1. DTCWT-ST:

It is the combination of multi-scale transforms and sparse representation of image fusion. DTCWT also helps in performing transforms properly not only comparability.
2. MERTERNS:
It is used to contrast the local criteria for fusion.
3. PROPOSED:
The coefficients of images are to generate JND threshold and also low sub bands are fused in the same manner.
The images represent typical visible fusion scenarios and higher frequency visible fused with high luminance thermal IR areas.
By these adjusted coefficients increases the contrast with in these regions so that they retain the same level for perceptual fusion.

V. EXPERIMENTAL RESULTS



Fused Image

VI. CONCLUSION

The relationship between coefficient magnitude and perceptual importance is assumed. The perceptual importance of coefficients within image fusion is performed objectively and subjectively across a representative dataset.

In this it does not contain not only main perceptual information but also the retained information is arrived with in the original information.

92% information is retained in the original image after the image fusion.

Because of algorithms and parametric variations the results should be used to gain a sense of direction by fusion.

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