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Research Article

Image Segmentation of Multi-focused Images using Watershed Algorithm

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Abstract

Segmentation algorithm plays a vital role in region based image fusion process. Features should be segmented as single regions. Feature may split into more than one region and each region has to be treated separately. If possible, less number of regions should be generated to reduce the computational burden. Segmentation can be done either separately (uni-model segmentation) or jointly (joint segmentation). Uni-model segmentation method may create many regions than joint segmentation since different images have different features [4]. The challenge of finding small targets in big images lies in the characterization of the background clutter.. In this paper we report that it is possible to identify or mark the foreground objects and background locations by using watershed transform. By computing the segmentation function, foreground markers and background markers, we can achieve the modified segmentation function so that it has minima at the foreground and background marker locations.

Keywords: *Features, Foreground objects, Foreground markers, Background marker, Segmentation function, Watershed transform.*

1. Introduction

1.1 Image Segmentation

One level higher than the pixel level image fusion is feature level image fusion in which image is segmented to regions and the corresponding regions are fused. Feature is more important than the single pixel. Hence it is better to incorporate the feature information in the fusion process. Segmentation algorithm plays a vital role in region based image fusion process. Features should be segmented as single regions. Feature may split into more than one region and each region has to be treated separately. If possible, less number of regions should be generated to reduce the computational burden. The information flow diagram of image segmentation algorithm is illustrated in Fig- 1. Segmentation can be performed by applying DTCWT and watershed transform. The segmented images are used in the feature level image fusion process. The DT-CWT provides the six sub bands oriented at ±15, ±45, ±75. Complex wavelets are shift invariant and retain the properties of scale and orientation sensitivity. Image segmentation is the process of separating out mutually exclusive homogeneous region of interest. DT-CWT is used to detect the texture boundaries.

1.2 Texture representation

Generally, Gabor filter had been used to for texture representation because of facts from psychophysical experiments. Human visual system decomposes the visual field into perceptual channels. These channels are evenly spaced in angle. Gabor filter representation is computationally burdensome. Complex wavelets are alternative to Gabor functions for texture analysis. Complex wavelets are shift invariant and retain the properties of scale and orientation sensitivity. The detail coefficients of dual tree complex wavelet transform is used for texture process. Denoting the detail coefficients at level i, orientation θ by $D_{i,\theta}(x,y)$ and retain the complex magnitude $|D_{i,\theta}(x,y)|$ for further analysis.

1.3 Texture post processing

Simple gradient calculation of complex magnitude gives rise to a double edge in the gradient magnitude. Application of watershed algorithm produces a spurious narrow region along the boundaries. It can be avoided using median filter before gradient operator. Median filter is edge preserving smoothing filter that can suppress isolated noise without blurring sharp edges. Specifically the median filter replaces a pixel by the median of all pixels in the neighborhood and it is computationally burdensome. The solution is separable median filter and it has to be chosen with care, the first filter removes the double edge effect of the second filter parallel to sub band orientation removes noise of the sub bands. Considering both scale and orientation, the sub band resulting from the filtering is

$$S_{i,\theta}(x,y) = MedFilt\left(MedFilt_{(\theta+0.5\pi)}\left(|D_{i,\theta}(x,y)|\right)\right) \qquad (1.1)$$

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The order of the median filter is chosen as (7+2n), where n is the current level of the wavelet transform and the constant term is equal to the size of wavelet filters. ‘’

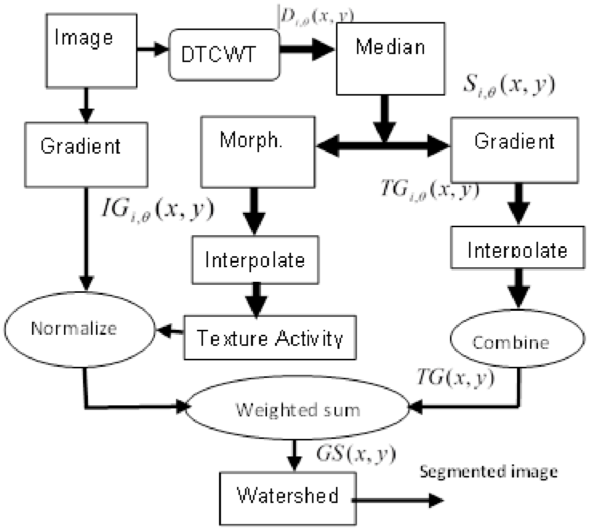

Fig-1 Information flow diagram of image segmentation algorithm

1.4 Texture gradient

Gaussian derivative function is used as gradient operator. The texture gradient magnitude of each sub band is

$$TG_{i,\theta}(x,y)=\sqrt{\left(S_{i,\theta}(x,y)*G_x^{'}\right)^2+\left(S_{i,\theta}(x,y)*G_y^{'}\right)^2} \quad (1.2)$$

Where $G_x^{'}$ and $G_y^{'}$ are the Gaussian partial derivative filters in x and y directions and *denotes convolution.

Weighted sum of the magnitudes is

$$TG(x,y)=\sum_{i,\theta}\mathrm{interp}\left(w_{i,\theta}\mathrm{x}TGH_{i,\theta}(x,y)\right) \quad (1.3)$$

Where $TGH_{i,\theta}(x,y)=\dfrac{TG_{i,\theta}(x,y)}{\max\left(TG_{i,\theta}(x,y)\right)}$

$$w_{i,\theta}=\frac{N_i}{\sum_{x,y}TGH_{i,\theta}(x,y)^2}$$

N_i : number of pixels in sub band at level i

$\mathrm{interp}()$: Interpolation function

Up sampling is done using interpolation and it is performed separable.

1.5 Gradient Combination

Texture and intensity gradients are combined to get final gradient capturing all perceptual edges in the image. The combined gradient will be dominated by intensity gradient in smooth regions and texture gradient in textured regions. The activity measure is

$$activity(x,y)=\exp\left(R_{half}\left(\frac{E_{tex}(x,y)}{\alpha}-\beta\right)\right)$$

(1.4)

Where $\alpha=2$ & $\beta=7$ are chosen based on intuition

$R_{half}(\varsigma)$ is the half wave rectification to suppress the negative exponents as:

$$R_{half}(\varsigma)=\begin{cases}0: & \varsigma<0\\ \varsigma: & \varsigma\ge 0\end{cases} \quad (1.5)$$

Texture energy E_{tex} is calculated on up sampled sub bands. Texture features respond slightly larger area than the desired because of the involved spatial integration. Morphological erosion E is used to overcome the problem and strel used in this function is a square neighborhood of nine pixels. The texture energy is computed as

$$E_{tex}=\sum_{i,\theta}\mathrm{interp}\left(E\left(\frac{S_{i,\theta}(x,y)}{2^i}\right)\right) \quad (1.6)$$

The denominator 2^i is used to correct the DC gain of the wavelet filters. Finally, the weighted sum of texture and modulated intensity gradient is computed as

$$GS(x,y)=\frac{|IG(x,y)|}{activity(x,y)\mathrm{x}w_I}+\frac{TG(x,y)}{w_T} \quad (1.7)$$

Where w_I is to be four times the median intensity gradient

w_T is the median value of the texture gradient

2. Watershed transform

In geography watershed is the ridge that divides areas drained by different river systems. A catchment basin is the geographical area draining into a river shown in Fig- 2. The watershed transform applies these ideas to gray-scale image processing in a way that can be used to solve a variety of image segmentation problems. Separating touching objects in an image is a difficult task. Watershed transform is often used to solve this type of problem. Watershed transform detects catchment basins and watershed ridge lines in an image by treating it as a surface where light pixels are high and dark pixels are low.

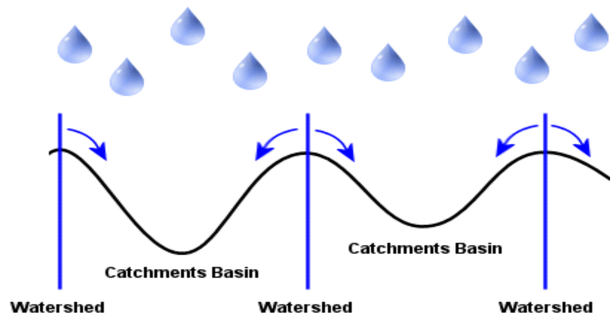

Fig- 2 Watershed Transform

If it is possible to identify or mark the foreground objects and background locations then the segmentation using watershed transform works well. Marker-controlled watershed segmentation has the following steps :

1. Compute a segmentation function. This is an image whose dark regions are the objects to be segmented.
2. Compute foreground markers. These are connected blobs of pixels within each of the objects.
3. Compute background markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it has minima at the foreground and background marker locations.

5. Compute the watershed transform of the modified segmentation function.

The gradient magnitude is used as the segmentation function; use the Sobel edge masks, imfilter to calculate the gradient magnitude. The gradient is high at the borders of the object and low inside the object. To mark the foreground objects we are using the morphological technique called opening-by-reconstruction and closing-by-reconstruction to clean up the image, these operations will create flat maxima inside each object that can be located using imregionalmax. To mark the background in the cleaned up image, the dark pixel belongs to background, use the thresholding operation. The background pixels are in black, but ideally we don't want the background markers to be too close to the edges of the objects we are trying to segment. Well thin the background by computing the watershed transform. Here we used the watershed segmentation using the distance transform . The distance transform of a binary image is a simple concept. It is the distance from every pixel to the nearest non-zero valued pixel. Note that 1-valued pixels have a distance transform value of 0. The distance transform can be computed by using the matlab function 'bwdist'. The following example shows how the distances transform works, Table 1 gives binary image matrix and Table 2 gives corresponding distance transform.

Table 1: Binary image matrix

1	1	0	0	0
1	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	1	1	1	0

Table 2: Distance transform matrix

1	1	0	0	0
1	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	1	1	1	0

3. Results and Discussions of segmentation of images

The image to be fused (vis.bmp and ir.bmp) is shown in Fig-3. The intensity gradient $IG(x, y)$ is shown in Fig- 4. Edges are highlighted than smoothing areas. Modulated intensity image i.e ; after suppressing the edges within the textured region is shown in Fig- 5. The textured gradient image is shown in Fig- 6. The edge of the textured region is high contrast than other non-textured regions. The man is highlighted. Fig- 7 shows the weighted combination of texture and modulated gradients. The segmented image using the watershed algorithm is shown in Fig- 8. The watershed algorithm directly often results in over segmentation. This over segmentation can be avoided using marker controlled watershed algorithm. The final segmentation map and segmented image are shown in Fig- 9. The important features like man in the image are perfectly segmented.

Fig- 3 The images (vis.bmp and ir.bmp 137*181*3)

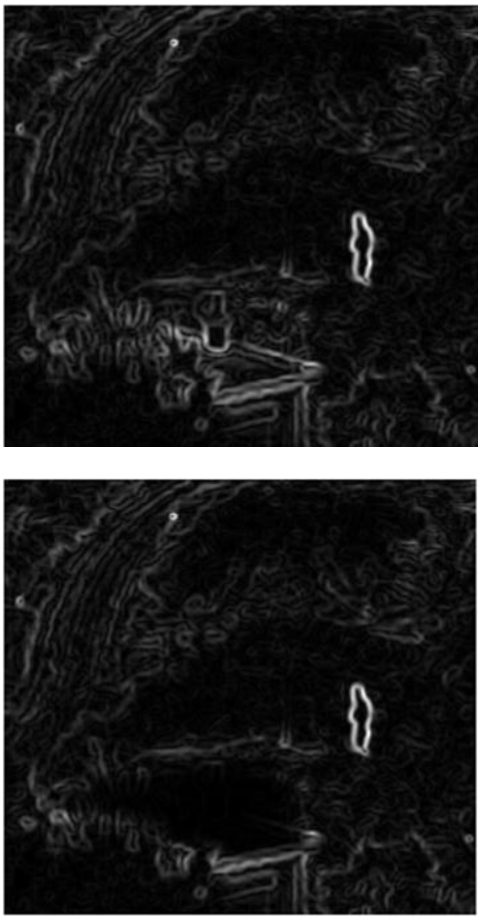

Fig- 4 Intensity gradient image

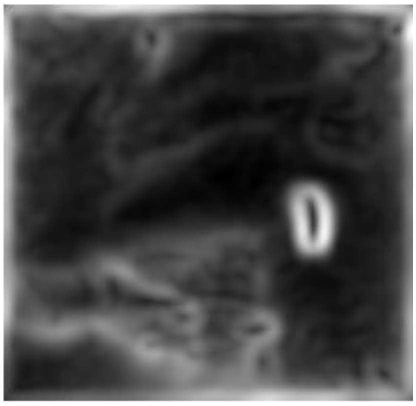

Fig- 5 Modulated intensity gradient image

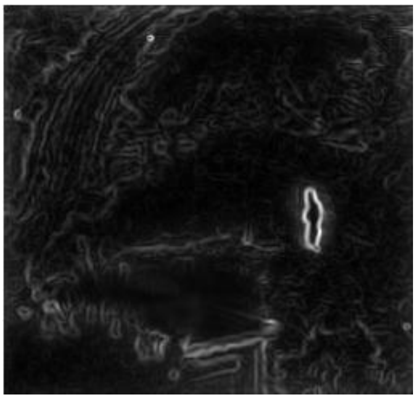

Fig-6 Texture gradient

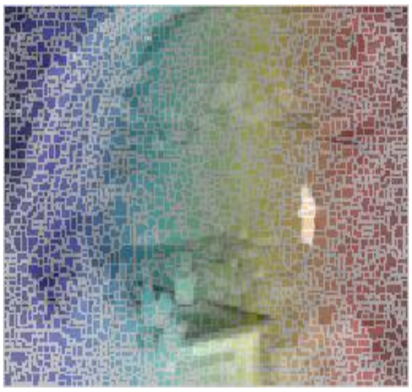

Fig-7 Combined gradient image

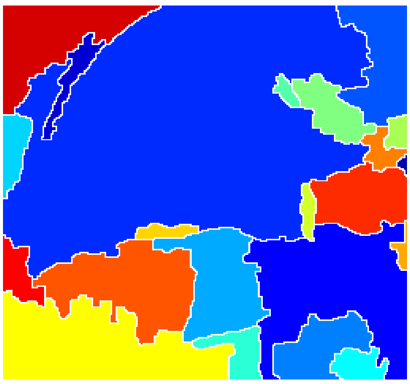

Fig- 8 Segmented image using watershed algorithm

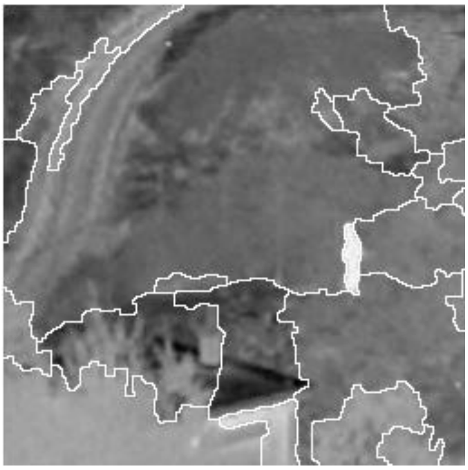

Fig- 9 Segmentation map and segmented image (infrared image)

In region based image fusion procedure, the images to be fused should be segmented. Let the images to be fused are infrared (ir.bmp) and visible (vis.bmp). There should be a single segmentation map for both the images. It could be possible by combining the individual (uni-model) segmentation maps. The segmentation map of the infrared image is already shown in Fig- 9 and the segmentation map of visible image is shown in Fig- 10. The combined segmentation map is shown in Fig-11. One can observe that there are many segments and hence it take more computational time. As mentioned earlier, this problem can be solved by joint segmentation.

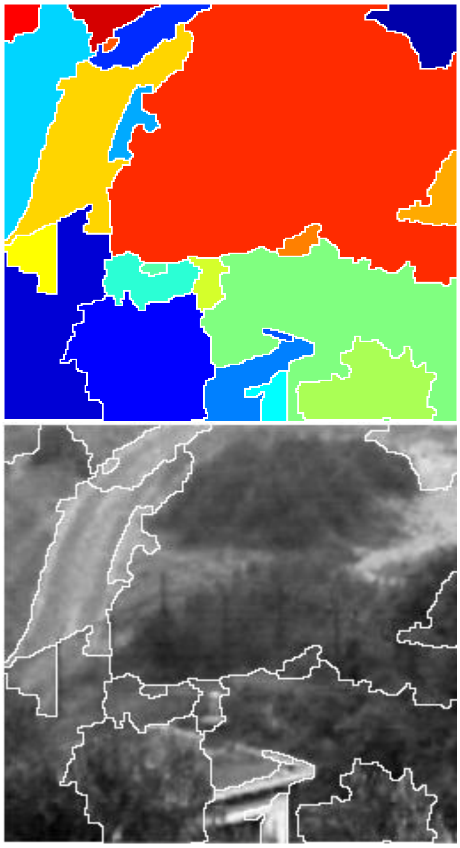

Fig- 10 Segmented image (visible image)

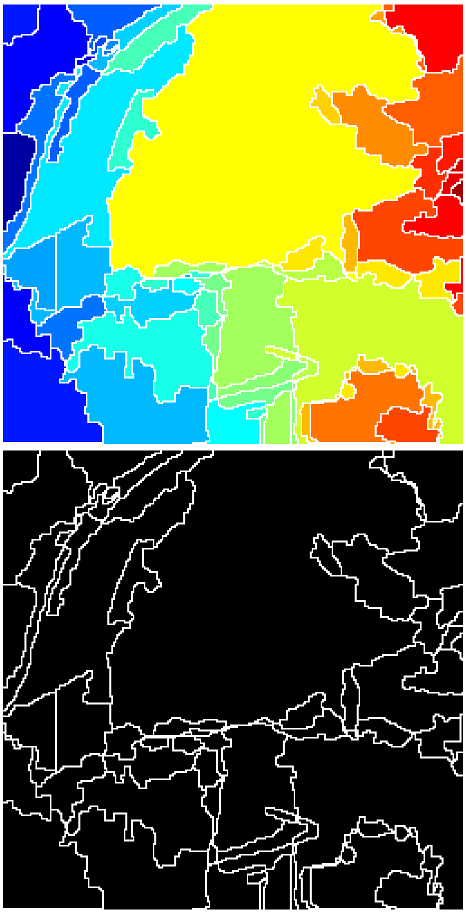

Fig- 11 Combined segmentation map

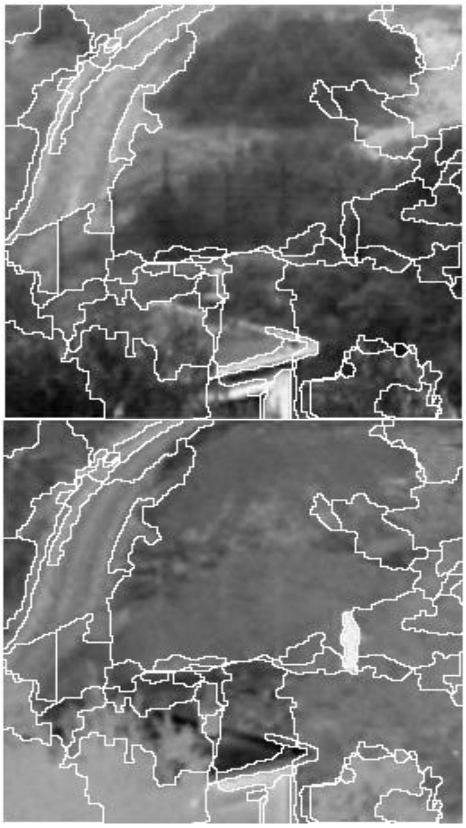

Fig- 12 Segmented visible and infrared images

The segmentation map shown in Fig- 11 is super imposed on visual and ir image and the corresponding segmented image shown in Fig- 12

3.1 Joint Segmentation

Let the weighted sum of the texture and modulated intensity gradients of the infrared image is $GS_{ir}(x,y)$ and of the visible image is $GS_{vi}(x,y)$.
These two individual gradients are combined as:

$$GS = \frac{GS_{ir}(x,y)}{median(GS_{ir}(x,y))} + \frac{GS_{vi}(x,y)}{median(GS_{vi}(x,y))} \qquad (3.1)$$

The marker controlled watershed algorithm is applied on this combined gradient image. The joint segmentation map is shown in Fig- 13. It is observed that the number of segments is less compare to previous technique and important features are segmented clearly. Clearly by using joint segmentation number of segmentation regions can be reduced, if the numbers of regions are more computational time increases i.e. it takes more time to fuse the regions.

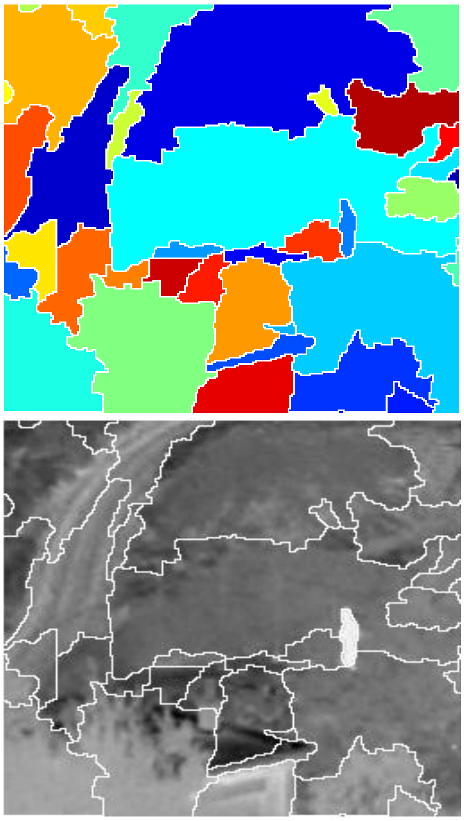

Fig- 13: Joint segmented image

4. Feature Level Image Fusion

One level higher than pixel level image fusion is feature level image fusion. One technique of achieving this is with a region based fusion scheme. Initially an image is segmented to produce a set of regions. Various region properties can be calculated. The properties can be used to determine which features from which images are used in the fused image. Feature level image fusion has some advantages over pixel level image fusion as more intelligent semantic fusion rules can be considered based on actual feature in the image rather than on single pixel. Feature is very important than the actual pixel. Hence it is better to incorporate the feature information in the process of fusion. Segmentation algorithm plays a vital role in region based image fusion process. Features should be segmented as single regions. Feature may split into more than one region and each region has to be treated separately. If possible, less number of regions should be generated to reduce the computational burden. The block diagram of feature level image fusion is as shown in Fig- 14. The input images are joint segmented by using DTCWT and watershed transform as discussed in chapter 3 (Image segmentation). The joint segmented image is shown in Fig- 13 is used as the segmentation map. By using the segmentation map we are calculating the salient feature like standard deviation, if the standard deviation of the segmented part of the input image I_1 is greater than the standard deviation of the segmented part of the input image I_2 then the fused image part comes from input image I_1, otherwise it is from input image I_2. Fig-15 shows the segmented part of visible and infrared images. The fused image without filter as some ridge lines is as shown in Fig- 16(a) this can be reduced by using the matlab function imfilter. The fused image with filter is as shown in Fig- 16(b).

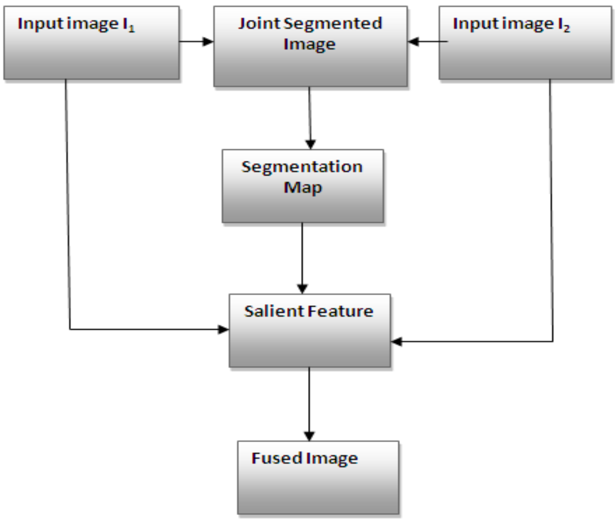

Fig- 14 Block Diagram of Feature Level Image Fusion

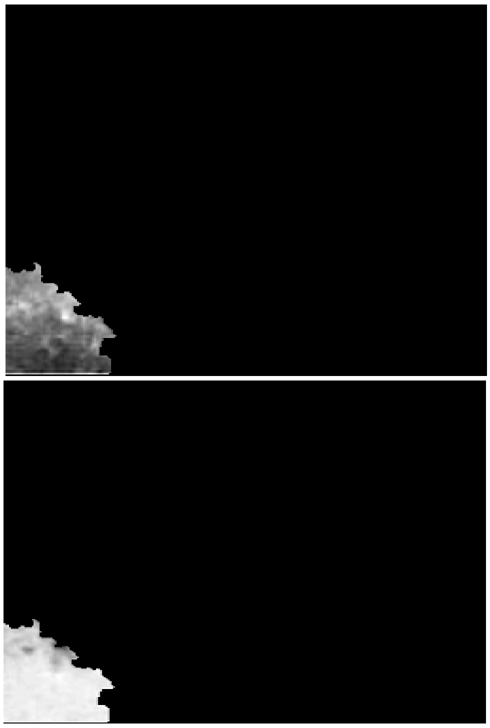

Fig- 15 Example of Segmented part of visible and infrared images

(a) Without filter

(b) With filter

Fig- 16 Fused images

The above fusion is based on the spatial domain, for the wavelet domain consider Fig-4.2 shows the segmented part of visible and infrared image for that we are calculating the wavelet coefficients by using DT-CWT , if the standard deviation of segmented part of input image I_1 is greater than the standard deviation of segmented part of input image I_2 then the wavelet coefficients comes from input image I_1, otherwise wavelet coefficient from input image I_2. After that perform the inverse dual tree complex wavelet transform to get the fused image shown in Fig- 17

Fig- 17 Feature level fused image (Wavelet Domain)

5. Conclusion

From this study, it is concluded that Watershed transform provides a good fused image at the cost of execution time and also it requires a good segmentation map. Most of the time DT-CWT provides good fusion results since it considers the edge information in six directions. In all cases, the DWT based pixel level image fusion algorithm does not provide good results since it does not consider the edge information and lack of shift invariant. Watershed algorithm based image fusion algorithm provides good results in some cases where there are no much edges in the images to be fused, it is shift invariant and it does not consider the directional edge information. Only standard deviation is used as a salient feature to select the best segment. More salient features can be used along with some fuzzy logic or neural networks to choose the best segment. It can also be extended for colour image fusion.

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