



Image Fusion using Discrete Wavelets Transform

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Abstract— *This paper explains brief algorithm of image fusion using discrete wavelet transform, Where spatial and spectral both information were preserved in the fused image.. We have developed a robust technique to merge two multi focused images in to the one using wavelet transform. Image fusion achieved with DWT lifting scheme proves to be better than existing Image fusion techniques.*

Keywords— *Image fusion, Image processing, Wavelet transform*

I. INTRODUCTION

Image fusion is the process of combining relevant information from minimum two images into a solo image ^[1]. The aim of this algorithm is that the resulting image will be more informative than the input image. Algorithm will be useful in remote sensing applications, the increasing availability of image sensors in space. Mostly in image processing we require high spatial and high spectral resolution in a single image but the available equipment are not capable of providing such data convincingly. Image fusion techniques allow the integration of different information obtained from different image sources. The fused image can have complementary spatial and spectral resolution characteristics ^[1]. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging ^[1]. In our algorithm we try to merge the features that appear in one source image ^[2] but not in others. They are rendered in such a way that they reduced contrast or superimposed on features from other images.



Fig. 1 Example of multi-focused image where top two image has only one toy in focus and bottom image has front most and rear most toy in focus.

II. LITERATURE SURVEY

The development of new multi imaging sensors has brought a need for image processing techniques. This technique should effectively fuse images from different sensors into a single image for interpretation [3]. Till now the image fusion has been considered primarily as a means for presenting images to humans. It may also be expected that fusion can become equally important in combining images, and hence in compressing source image data, for interpretation by computer vision systems saving the space [3]. An image fusion technique is successful to the extent that it creates a composite that retains all useful information from the source images, and does not introduce any noise that could interfere with interpretation.

The most direct approach to fusion is to sum and average the two source images but this produces unsatisfactory results.

Some of the most promising approaches to fusion are those that perform image combination in a pyramid transform domain: An image pyramid is first constructed for each source image, then a pyramid is formed for the composite image by selecting coefficients from the source image pyramids. Finally, the composite image is recovered through an inverse pyramid transform [4]. Several variations on pyramid-base fusion have been described in the literature [5]. These methods generally appear to provide good results. One limitation is in the fusion of patterns that have roughly equal salience but opposite contrast. This is a pathological case since image averaging results in pattern cancellation, and selection is unstable [6]. In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information [1].

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on uniform rational filter bank [7], Laplacian pyramid [8] and one which we are using in this algorithm Discrete Wavelet Transform.

III. METHODOLOGY

Algorithm consists of steps which are described as follows:

Collect composite images taken with different depth-of-fields so that a resultant focus image is generated. Different input arguments are para for parameters, image type which can be grey scale images (MxN) and rgb colour images (MxNx3), fname for file names of input images. The output arguments for the program are kept as J which is a fused image. Different parameters are the total number of decompositions, which we took as 6

with our algorithm, weight propagation among subbands from parent to children, which by default we set to 1, smoothing at each subbands for noise reduction again set to 1 by default, show debug message for user to see message. The number of images is the input from the user taken by algorithm and by default we set it to two. Total number of decomposition affects the time of execution but also improves the accuracy. Wavelet decomposition for the Y component from YCbCr colour space is carried out. Debug messages such as 'Reading images and applying wavelet to them' are displayed during the execution of algorithm. In next step all the images are read and RGB colour images are converted into the YCbCr colour images. Next step is to initialization of the coefficient array to all zeros. After generation of blank array new weight matrix array and subbands are generated. For colour images wavelet decomposition for the Cb of YCbCr is carried out where as for grayscale image this step is not required. Similarly wavelet decomposition for the Cr of YCbCr is carried out in next step if image is colour. Next step is to generate J image which was achieved as follows: Take input from user as total number of decompositions by default is kept 6 after varying it from 1 to 16 we found optimum results were obtained at 6. In next step weight propagation among subbands from parent to children is assigned. Weight smoothing at each subband is optional step. By default debug messages were kept hidden. For proper operations image needs to be converted to 'double' from uint8.

W which is 3D weight matrix is of the size (C, S) where C is wavelet coefficient image and S is wavelet subbands size. For denoising image Gaussian low pass filter of size 3, 3 was used which is almost a box filter. Next step is converting a map of usage index to a ratio map where coefficients are being converted as weights. Wavelet parents-to-child relationship is basically reweighting DC sub-bands from children to parent. Next step is to create the weight map of the approximation coefficient sub-band. Gaussian filter used to denoise is symmetric.

Next step in algorithm is deblur detail sub-bands by passing up and conversing the weight vectors. Here we need to interpolate to avoid showing 'divide by 0' error. Next step is to make new sub-bands filled up with focused coefficient. Wavelet transform used here includes: The size of output image obtained from the specified decomposition level. Next step is taking log to the base 2 and flooring the value. Now we extended image symmetrically. Once image is extended we performed the multi stage 2D wavelet decomposition using lifting scheme, where approximation coefficients of the image and number of decomposition level were the inputs to the algorithm from previous steps. Output argument were coefficient Image and size of the image with margin from top and left of each subbands. Margins were created by image padding with zeros. Decomposition function uses equal weightage from all input images. Scale factors selected were 1.15. Next step is to perform the multi stage 2 dimensional wavelet reconstruction using lifting scheme. Finally reconstructed image is shown in J variable and double to uint8 conversion was used for proper display of image.

IV. RESULTS

Figure 2 shows rear clock in focus as one of the input to the algorithm and Figure 3 shows same two clocks but this time front clock is in the focus. These two images were taken as the input images to our algorithm



Fig. 2 Input image showing rear clock in focus and front clock is out of focus.



Fig. 3 Input image showing front clock in focus and rear clock is out of focus.

Figure 4 shows the resultant image which is fused. The resultant image gives more information than input images.



Fig. 4 Final output image after image fusion.

The above algorithm was tested with 30 different multifocused images including 20 colour and 10 grayscale images. Different parameters computed for resultant images were shown as in Table I where current algorithm is in last row.

TABLE I
COMPARISON OF DIFFERENT IMAGE FUSION ALGORITHMS

	Mean	Standard deviation	Average Gradient	Entropy	Mean information	Fusion Symmetry	Correlation	Noise
Mean ^[9]	97.273	49.346	3.69	7.26	5.296	1.84	0.989	0.001
Maximum ^[10]	101.037	50.197	3.63	7.27	7.467	1.84	0.98	0.327
DWPT(mean – max) ^[11]	97.076	49.513	5.108	7.282	4.977	1.838	0.985	0.141
DWPT ^[12]	97.827	50.114	5.685	7.305	3.962	1.632	0.979	0.368
CV T(mean – max) ^[13]	98.565	49.119	4.566	7.414	4.007	1.838	0.985	0.092
CV T ^[13]	99.147	52.078	5.807	7.425	4.319	1.733	0.98	0.387
CNT(mean – max) ^[14]	97.097	50.117	8.538	7.468	3.885	1.871	0.972	0.158
CNT ^[14]	98.923	49.906	8.56	7.478	3.726	1.843	0.97	0.158
DWT Algorithm	97.131	49.503	4.653	7.362	4.027	1.860	0.986	0.209

V. CONCLUSIONS AND FUTURE SCOPE

This algorithm mean pixel value falls in same range as that of most popularly used image fusion algorithms. Standard deviation is improved for almost all algorithms except mean but entropy is better than mean. Although the mean information is reduced correlation with input images are still very high. Fusion symmetry and noise proves to be better than most of the other algorithms currently in use. There are many applications of image fusion; few of them are listed below:

- IR and visible images may be fused as an aid to pilots landing in poor weather.
- Infrared and UV images for night of blind^[15] vision
- CT and NMR images may be fused as an aid to medical diagnosis ^[16].

ACKNOWLEDGMENT

We would like to thank our head of the department Dr. K. B. Khanchandani for the support. We would also like to thank our principal Dr. V. N. Gohokar for his support and motivation. We would like to take this opportunity to thank all the staff and management of Shri Sant Gajanan Maharaj College of engineering for facilities and infrastructure provided to carry out this research work.

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