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Combined Denoising and Fusion of Multi Focus images

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***Abstract*— Due to the limitation of depth of field in CCD devices which are used to capture the image of the scene of interest, it is impossible to get an image that contains all relevant objects in the scene in focus. A possible solution to bring all objects in the scene in focus is image fusion. And also images are often corrupted by noise due to errors generated in imaging sensors. So, it is important to eliminate noise in the images before some subsequent processing. In this paper, it is proposed to denoise the images using Decision Based Algorithm for Removal of High-Density Impulse Noises (DBAIN) method in spatial domain followed by fusion using Higher Density Discrete Wavelet Transform (HDWT) to form the multi focused images.**

***Keywords*— Image Denoising, Image Fusion, DBAIN and HDWT.**

I. INTRODUCTION

The driving forces in today's manufacturing environments are quality improvement, cost reduction, increased volume of production and shorter cycle times of manufacturing. The quality of many raw materials, parts, and products can be measured by electrical or mechanical means or by visual inspection. Inspection by eye is costly, subjective, qualitative, inaccurate, eye-straining, and time consuming. For high speed and real time applications, manual inspection is not possible. Therefore, more and more manufacturers look for fast, accurate, reliable, and consistent machine vision system for automated visual inspection of their products. Machine Vision involves acquisition of the image of an object of interest followed by processing and interpretation of this image using computer for useful applications like inspection of quality of raw materials, parts and products in industries. The first step in machine vision is to acquire the images of objects in the scene. When the images of objects in the scene are taken from the camera, only the objects within the depth of field of camera are clearly focused and the other objects in the scene will be blurred. To get the image in which every object in the scene is focused, there is need to fuse the images taken from the same view point with different focus settings. The resulting composite image, called as fused image, will contain clear images of all objects in the scene. This is known as multi-focus image fusion. There are a number of methods for multi-focus image fusion. These methods are based on the assumption that images are noise-free. However, in practical situations, images are often corrupted by noise in image acquisition or transmission. Thus, it is necessary to investigate joint fusion and denoising of noisy multi-focus images. In this paper, it is proposed to denoise the images corrupted by Salt and Pepper Noise using Decision Based Algorithm for Removal of High-Density Impulse Noises (DBAIN) method in spatial domain followed by fusion using Higher Density Discrete Wavelet Transform (HDWT) to form the multi focused images.

II. IMPULSE NOISE IN IMAGES

Digital Images are often corrupted by Impulse noise which is always independent and uncorrelated to the image pixels and is randomly distributed over the image. So, unlike Gaussian noise, in impulse noise corrupted image, not all the image pixels are noisy, but small number of image pixels will be noisy and the rest of pixels will be noise free. There are different types of impulse noise namely fixed valued impulse noise, also called as salt and pepper noise, and random valued impulse noise. The salt and pepper type of noise is easier to restore whereas random valued impulse noise is somewhat difficult. In salt and pepper type of noise the noisy pixels takes either salt value (225) or pepper value (0) and it appears as black and white spots on the images. If p is the total noise density then salt noise and pepper noise will have a noise density of p/2.This can be mathematically expressed by

$$y_{i,j} = \begin{cases} 0 \text{ or } 255 \text{ with probability } p \\ x_{i,j} \text{ with probability } 1 - p \end{cases} \quad (1)$$

where y_{ij} represents the noisy image pixel, p is the total noise density of impulse noise and x_{ij} is the uncorrupted image pixel. In case, if salt noise and pepper noise may have different noise densities p1 and p2, then the total noise density will be p=p1+ p2 .In case of random valued impulse noise, noise can take any gray level value from zero to 225. In this case, also noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same. This can be mathematically expressed by,

$$y_{i,j} = \begin{cases} n_{i,j} \text{ with probability } p \\ x_{i,j} \text{ with probability } 1-p \end{cases} \quad (2)$$

where n_{ij} is the gray value of the noisy pixel.

III. IMAGE FUSION TECHNIQUE

The image of a scene formed by an optical system used in machine vision contains information about the distance of objects in the scene. Objects at a particular distance are focused whereas other objects are defocused or blurred by different degrees depending on their distance. This is shown in figure1. The point, P, on the object plane is clearly focused and perfectly imaged as point P', on the image plane. For a camera with a lens of focal length 'f', the relation between the position of a point close to the optical axis in the scene and the position of its focused image is given by the well known lens formula

$$\frac{1}{f} = \frac{1}{U} + \frac{1}{V} \quad (3)$$

where U is the distance of the object, and V is the distance of the image.

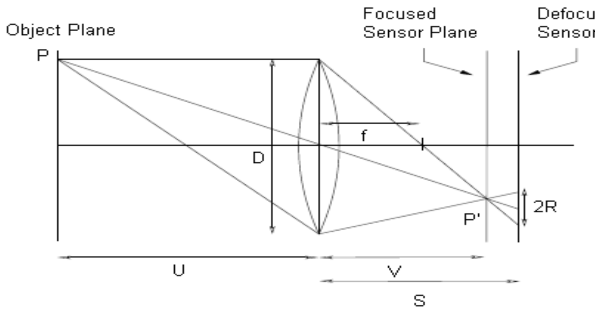

Fig 1: Model of Lens System

Therefore, in the image formed by a camera, only objects at a certain distance are in focus; other objects are blurred by varying degrees depending on their distance. Further, each lens must have a finite aperture of diameter D, which can be used to estimate radius of the blur circle induced as

$$\frac{D}{V} = \frac{2R}{S-V} \quad (4)$$

where S is distance between sensor plane and the lens. Then the depth of field of a lens system can be given as,

$$DOF = U_{far} - U_{near} \quad (5)$$

$$U_{far} = \frac{Uf(1-2\frac{R}{D})}{f-2\frac{R}{D}U} \quad (6)$$

$$U_{near} = \frac{Uf(1+2\frac{R}{D})}{f+2\frac{R}{D}U} \quad (7)$$

where U_{near} and U_{far} are the distances to the nearest and farthest object planes with blur circles less than or equal to the chosen R and U is the distance to the in-focus object plane. Due to limited depth of field of lens, it is possible to take clear image of the objects in the scene which are in focus only. The remaining objects in the scene will be out of focus. A possible solution to bring clear images of all the objects in the scene is to combine several pictures taken by the camera with different focus points into a composite image. The resulting composite image, called as fused image, will contain clear images of all relevant objects in the scene. This is known as multi-focus image fusion. There are two approaches to image fusion, namely Spatial Fusion and Transform fusion. In Spatial fusion, the pixel values from the source images are summed up and taken average to form the pixel of the fused image at that location. Transform fusion uses pyramid or wavelet transform for representing the source image at multi scale [4, 5]. The most commonly used wavelet transform is critically sampled Discrete Wavelet Transform (DWT) which can be implemented using perfectly reconstructed Finite Impulse Response filter banks. But, critically sampled DWT suffers from four shortcomings namely Oscillations, Shift variance, poor directionality and aliasing. Shift variance in critically sampled discrete wavelet transform exists due to down sampling during analysis and up sampling during synthesis [1, 2]. Improved performance can be found using an over complete or redundant wavelet transform in variety of signal and image processing applications. For example, the Undecimated Discrete Wavelet Transform (UDWT), which is expansive by the factor 3J+1, when J scales are implemented, shows improved results due to its shift invariant property. Complex Wavelet Transform (CWT) is also an alternate and complex valued extension to DWT with limited redundancy. CWT uses complex valued filtering that decomposes the real or complex signal into real and imaginary parts in transform domain [14-19]. It is approximately shift invariant and directionally selective in higher dimensions. It achieves this with a redundancy factor of only 2^d for *d*-dimensional signals, which is lower than the UDWT. The double-density discrete wavelet transform (DDWT) which provides a compromise between the UDWT and the critically-sampled DWT is two-times expansive, regardless of the number of scales implemented. Even so, the DDWT is approximately shift-invariant [10]. Like the CWT, the DDWT is redundant by a factor of 4 for two dimensions, independent of the number of levels. These above said expansive transform do not increase the sampling with respect to frequency or scale. An expansive dyadic wavelet transform, namely High Density Discrete Wavelet Transform (HDWT) over samples both space and frequency by a factor two [11]. This paper uses HDWT to fuse the denoised images.

IV. DBAIN Algorithm for Image Denoising

Decision Based Algorithm for Removal of High-Density Impulse Noises (DBAIN) method in spatial domain is a recently proposed algorithm to remove salt and pepper noise. In DBAIN, each Pixel is processed for de noising using a 3 X 3 window. During processing if a pixel gray scale value is '0' or '255' then it is processed, else it is left unchanged. In DBAIN, the corrupted pixel is replaced by the median of the window. At higher noise densities, the median itself will be noisy, and, the processing pixel will be replaced by the neighbourhood processed pixel.

Step 1) A 2-D Window of size 3×3 is selected. Assume the pixel to be processed is P(X, Y).

Step 2) the pixel values inside the window are sorted and the first element of the window is the Minimum value P_{min}, the last element of the Window is the Maximum value P_{max} and the middle element of the window is the median value P_{med}.

Step 3) *Case 1:* The P(X, Y) is an uncorrupted pixel if P_{min}< P(X, Y) <P_{max}, P_{min}>0 and P_{max}<255: the pixel being processed is left unchanged .otherwise P(X, Y) is a corrupted pixel. *Case 2:* If P(X, Y) is a corrupted pixel, it is replaced by its median value if P_{min}<P_{med}< P_{max} and 0<P_{med}<255. *Case 3:* If P_{min}<P_{med}< P_{max} is not satisfied or 255<P_{med}=0,then P_{med} is a noisy pixel .In this case, the P(X,Y) is replaced by the value of neighbourhood pixel value.

Step 4) Steps 1 to 3 are repeated until the processing is completed for the entire image.

V. Higher Density DWT

The higher density DWT is an expansive dyadic wavelet transform that over samples both space and frequency by a factor of two. Like DDWT, at each scale of HDWT, there are twice as many coefficients as the critically sampled DWT. However, HDWT also has intermediate scales; it has one scale between each pair of scales of the critically-sampled DWT. The 'over complete' wavelet basis associated with this expansive transform has two generators, $\psi_i(t)$, i = 1, 2. The spectrum of the first wavelet $\psi_1(\omega)$ is concentrated between the spectrum of the second wavelet $\psi_2(\omega)$ and the spectrum of its dilated version $\psi_2(2\omega)$ In addition, the second wavelet is translated by integer multiples of one half, rather than whole integers. The transform can be implemented with digital filter banks like the conventional DWT as shown in the following figure 2. Similar to DDWT, it uses three filters, one scaling and two wavelet filters. However, one of the wavelet filters is band pass instead of high-pass filters. And also the high pass filter is not down sampled and up sampled during analysis and synthesis. The analysis filter bank structure of HDWT is shown in fig 2. Therefore, the 2-D form of the HDWT is 5-times expansive.

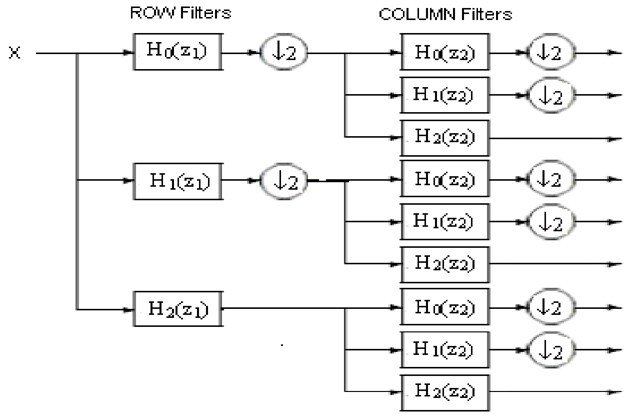

Fig 2: 2D Higher Density Discrete Wavelet Transform

VI. Proposed Work

A pair of source images focusing different objects in the scene of size 640 X 480 in GIF format is taken for study and is assumed to be registered spatially. A salt and pepper noise is added to each image in the pair and DBAIN algorithm is applied to restore the original image. Then, the images are transformed into wavelet domain by taking HDWT transform. There will be nine sub-bands for each image after HDWT was taken namely LL ,LB, LH, BL, BB, BH, HL, HB, HH, where L stands for 'low pass', H stands for 'high pass', and B stands for 'band pass'. To form the fused coefficient map for sub-bands of LB, LH, BL, BB, BH, HL, HB and HH, the wavelet coefficients from the source images whose absolute value is maximum was selected. For, LL sub band the fused coefficients are calculated as follows.

- Canny edge detector is applied to the LL sub band of the each source images.
- After the edge detection, region segmentation is performed based on the edge information using region labelling algorithm. In the labelled image, zero corresponds to the edges and other different value represents different regions in the image.
- The focus measure 'Spatial Frequency' is calculated as the activity level of region k in LL sub band of the each source images using the formulae [29],

$$SF = \sqrt{RF^2 + CF^2}$$

where

$$RF = \sqrt{\frac{1}{MXN}\sum_{x=1}^{M}\sum_{y=2}^{N}\left(f(x,y) - f(x,y-1)\right)^2} \text{ and}$$

$$RF = \sqrt{\frac{1}{MXN}\sum_{x=2}^{M}\sum_{y=1}^{N}\left(f(x,y) - f(x-1,y)\right)^2}$$

(8)

The approximation sub band of the fused image F is taken from the approximation sub band wavelet coefficients of source images whose activity measure in the particular region is high.

VII. Evaluation Criteria

There are four evaluation measures are used in this paper, as follows. The Root Mean Square Error (RMSE) between the reference image R and fused image F is given by [8],

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}[R(i,j) - F(i,j)]^2}{N^2}} \quad (9)$$

The Peak Signal to Noise Ratio (PSNR) between the reference image R and fused image F is given by [8],

$$PSNR = 10\log_{10}(255) \ / MSE \quad (10)$$

Quality index of the reference image (R) and fused image (F) is given by [7],

$$QI = \frac{4\sigma_{ab}ab}{(a^2 + b^2)(\sigma_{a^2} + \sigma_{b^2})} \quad (11)$$

The maximum value Q=1 is achieved when two images are identical, where a & b are mean of images, σ_{ab} be covariance of R & F, $\sigma_a{}^2$, $\sigma_b{}^2$ be the variance of image R, F. The Normalized Weighted Performance Metric (NWPM) which is given in the equation as [6],

$$NWPM = \frac{\sum \forall_{i,j} Q_{ij}^{AF} W_{ij}^{A} + Q_{ij}^{AF} W_{ij}^{B}}{\sum \forall_{i,j} W_{ij}^{A} + W_{ij}^{B}} \quad (12)$$

VII. Results

The performance of DBAIN algorithm for Denoising and HDWT for image fusion is measured in terms of RMSE, PSNR, QI & NWPM and the results are tabulated in table I. The results of combined Denoising and Image fusion are shown in figure 3. From the table, it is inferred that the proposed method for combined Denoising and Image fusion out performs the existing methods.

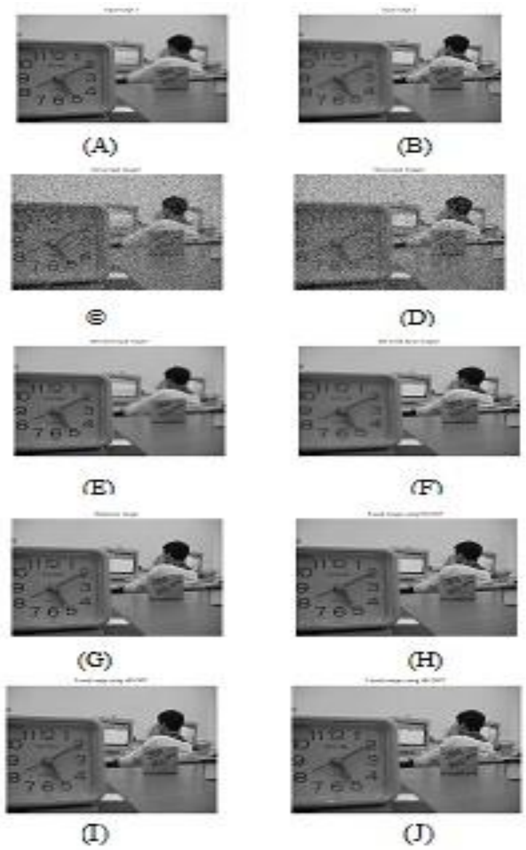

Fig 3: Results of Combined Denoising and Fusion

A & B. Input Images C &d. Noisy Images

E & F. Denoised Images G. Reference Image

H, I & J. Fused Images with Noise Density of 0.2, 0.4 & 0.6

TABLE I
Results of Combined Denoising And Fusion

Noise Density	0	0.2	0.4	0.6
RMSE	2.5737	4.0551	7.4751	10.9786
PSNR	39.6779	35.729	30.6039	27.7622
QI	0.9988	0.9966	0.9875	0.9729
NWPM	0.7009	0.6969	0.6246	0.5872

VIII. Conclusion

This paper presents new method for combined Denoising and fusion of multi focus images HDWT and their performance is compared in terms of various performance measures like RMSE, PSNR, QI and NWPM. Both DBAIN algorithms for image Denoising and HDWT for image fusion provide very good results both quantitatively & qualitatively. Hence using the above proposed method, one can enhance the image with high geometric resolution and better visual quality.

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