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REFLECTION REDUCTION USING SUPER RESOLUTION TECHNIQUE FOR QUALITY INSPECTION OF HIGHLY REFLECTIVE METAL

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ABSTRACT— *In case of manufacturing industries, quality inspection plays very important role. This process can be performed manually. But manual inspection can lead to number of errors. It is a risky process. It thoroughly depends on the patience of inspector. Therefore to automate the industrial inspection nowadays image enhancement techniques are being rapidly used. In quality inspection all dimensions of mechanical object are inspected. When machine products are manufactured, defect detection is also performed in the process of quality inspection. In case of metal surface which is having high reflection coefficient, defect detection becomes difficult. This reflection can act as a noise in image. Because of this reflection in image edge detection cannot be performed easily. Hence for processes like edge detection and defect detection, reflection reduction is highly required. The goal of proposed method is to design a right system for quality inspection to beat problem of reflection from metal body. In proposed algorithm super resolution technique is used for reduction of reflection. Wavelet transform is used to perform hard thresholding and soft thresholding. Quality evaluation is performed with the help of parameters like PSNR, MSE, SSIM and correlation.*

Keywords—**Reflection reduction, wavelet transform, hard thresholding, soft thresholding, super resolution etc.**

1. INTRODUCTION

Quality Inspection is an unavoidable part of every industry. Quality inspection can be done manually. Manual inspection completely depends on inspector's mood and skills. Hence this process is person dependant. Hence this process is not reliable. It can generate number of errors. So to avoid this problem, Now, numbers of industries are acquiring image enhancement technique to automate the process. Automated inspection is very helpful in automating manufacturing process. With the help of these techniques we can reduce errors as well as costs. Inspection is a method of determining whether the product fulfills all the requirements or not. It has been seen that, manual inspection cannot give 100% defect detection. Therefore, one can go for automated inspection to improve the quality of product and to improve defect detection process. Hence one can avoid problems arriving in next phases of manufacturing because of faulty defect detection. In automated inspection, generally machine vision techniques are used. Using these techniques, one can find out the properties of given metal job.

Metals like gold, aluminum, silver and copper etc. have very high reflection coefficient. At present, these metals are widely used in many areas. In number of industries like domestic electronics, communication industries, construction and automobile industries these metals are largely used as raw material. Because of this, surface quality of these metals matter a lot. It can directly affect the quality of final product. In case of highly reflective metal, detection of defects is very tedious job. If reflection is present in some area of image then inspection becomes extremely complex. It affects edge detection also. Light gets highly reflected from straight and circular edges. Then one cannot perform dimension checking. Hence there is highly requirement of designing a system which can reduce the reflection and smooth's the inspection process.

Super resolution technique can be used for reflection reduction. In wavelet two types of thresholding can be used for reflection reduction. These are hard thresholding and soft thresholding. If we apply wavelet transform on image gets decomposed in 4 sub bands, such as LL, LH, HL and HH. Approximation coefficients can be obtained from LL sub band. HL, LH, HH give detail coefficients. In that, HL provides horizontal details while vertical details can be obtained from LH band. HH band is for diagonal details. In this paper super resolution is performed first and it is followed by hard and soft thresholding to get final reflection reduced image.

2. PREVIOUS WORK

Pedro de Almeida [3] has proposed a method for reduction of reflection which is there in color images. Two rules are used for reflection identification. First rule is for thresholding. Pixels having

Average RGB component values (luminosity) more than 250 are said as reflections. Small as well as large white zones are present in NICE.I images. Therefore, second rule is required to mark the portions which are simultaneously white and very small, representing the reflections. Afterwards, every pixel with reflection gets replaced by average value of the darker half of the pixels which are positioned in a restricted circle around that pixel. Purpose of this method is to improve the detection of iris and pupil location. This method is not to get back original information that is covered by reflections.

Dae Sik Jeong, Jae Won Hwang and Byung Jun Kang [4] have proposed one method in which corneal specular reflection (SR) is used to divide image with reflection into two classes, good and bad detection. Pupil and iris regions can be detected correctly if detection is good. If detection is bad, they are wrongly detected. To perform this classification numbers of SR points are required to be counted in pupil as well as iris region. Generally, corneal SR has higher reflectance than others. Hence its gray level is more than others. Hence pixels having gray level more than 250 are taken as SR points. For good detection number of SR point is greater than one otherwise we can say it is bad detection.

Line intensity profile and a support vector machine method (LIPSVM) is proposed by Anis Farihan Mat Raffei[5]. In this method, green, blue intensities are subtracted from 255 i.e. higher intensity value. Pixel is reflected if blue and green pixel intensities are less than red intensity of it. Reflection classification is done by SVM. Training and testing is performed. '1' is used to represent reflected pixels while '-1' is used for non reflected one. Each reflected pixel gets replaced by nearby four neighbors present in non reflected area.

Chopade and Patil [22] proposed super-resolution scheme by the design of a specific class of dyadic-integer-coefficients based wavelet filter bank. The coefficient of this proposed scheme are integer and rational. So hardware implementation of this super resolution scheme becomes more suitable and it reduces computational complexity.

Demiel-Anbarjafari[8] proposed Super Resolution technique based on discrete wavelet transform (DWT) and stationary wavelet transform (SWT) which are used to decompose a low resolution image into

Different sub band images. Then the high frequency sub band images are interpolated using bicubic interpolation. In parallel, the input image is also interpolated separately. Finally, the interpolated high-frequency sub band images and interpolated input image are combined by using inverse DWT (IDWT) to obtain super resolved image.

3. PROPOSED METHOD

In this paper super resolution technique is used for reflection reduction. Super resolution is combination of blurred, low resolution images of same scene. It can be achieved through multiple and single frame image. In single frame super resolution, interpolation methods are used to obtain super resolved image. Here we proposed wavelet based super resolution algorithm for measurement of quality of images with reflection using different interpolation methods. Wavelet based hard thresholding and soft thresholding are applied on image to get reflection reduced image. In this method, first image of highly reflective metal is captured. Then it is converted into gray scale image. Now this image is taken as input image for further operations.
First SWT is applied on the image. It decomposes the image into four sub bands LL1, LH1, HL1 and HH1. SWT is different than DWT in case of sub bands. In SWT, all four sub bands have same size as that of original image. Before applying DWT, image is interpolated by 2. Then DWT is applied on input image to get approximation coefficients LL2 and detail coefficients HL2, LH2, HH2. Size of these sub bands is one fourth of the original image. Afterwards, super resolution technique is performed. Detail coefficients of both SWT and DWT are added to get resultant coefficients HL3, LH3, HH3. These coefficients are then interpolated along with approximation coefficients of DWT i.e. LL2. Nearest, spline, linear and cubic interpolations are performed. Finally IDWT is applied to get the image with super resolution. Then wavelet based hard thresholding and soft thresholding are applied. In this method, different interpolation techniques are applied on high frequencies sub bands to increase size of 1024×1024 so we obtained super resolved image of size 2048×2048. We applied nearest, spline, linear and cubic interpolations to sub bands to measure how high frequencies components preserves in super resolved image.

3.1 Hard Thresholding:

Hard thresholding is nothing but 'keep or kill' operation. In hard thresholding, if the pixel value is less than threshold T then we keep it as it is but if the pixel value is greater than threshold T then it is assigned to zero.

$$A(I,\lambda) = I \text{ For all } |I| > \lambda$$
$$= 0 \text{ Otherwise}$$

Where,

I = Pixel value

λ = Threshold value

3.2 Soft Thresholding:

$$A(I, \lambda) = \mathrm{sgn}(I)\ \max(0, |I| - \lambda)$$

Where,

I = Pixel value

λ = Threshold value

In soft thresholding, all pixel values above zero are shrinked instead of making them zero. This overcomes the drawback of hard thresholding.

4. RESULTS

Quality evaluation is performed using parameters like PSNR, MSE, SSIM and correlation.

1. **Peak Signal to Noise Ratio (PSNR):**

PSNR is maximum pixel intensity square to the MSE ratio.

$$PSNR = 10 * \log_{10} \frac{A^2}{MSE}$$

Where, A=maximum pixel value

2. Mean Square Error (MSE):

$$MSE = \frac{1}{r * c} \sum_{i=1}^{r} \sum_{j=1}^{c} (A(i, j) - B(i, j))^2$$

Where, A (i, j) = Original image

B (i, j) = Reconstructed image

In MSE reconstructed image is subtracted from original image to get the error. Average of these errors is taken to obtain the MSE.

3. Structural Similarity Index Measure (SSIM):

To perform similarity measurements, SSIM is used. In this luminance, structure and contrast these three parameters play very important role.

$$SSIM = \frac{(2 * mA * mB + C1)(2 * sIR + C2)}{(mA^2 + mB^2 + C1)(sA^2 + sB^2 + C2)}$$

Where, mA=mean intensity of original image

mB= mean intensity of reconstructed image

sA=standard deviation of original image

sB=standard deviation of reconstructed image

$C1 = (K1L)^2$ And $C2 = (K2L)^2$

Where K1<<1 and K2<<1

L=Dynamic range of pixel value.

4. Correlation:

Correlation parameter is used to find out correlation coefficient between reconstructed image and the original one.

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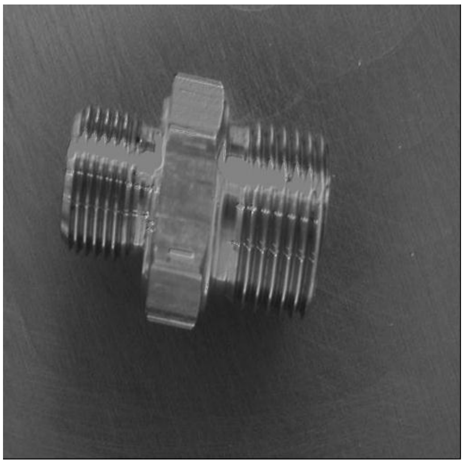
In this experiment, we applied hard as well as soft thresholding on resultant image to reduce reflection in the image. Resultant images obtained by proposed algorithm using hard as well as soft thresholding are shown in figure1 and figure2.

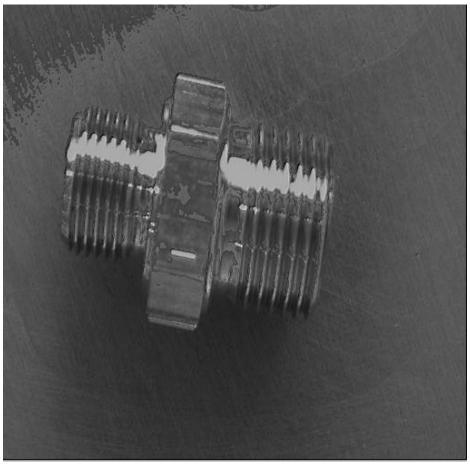
(a)



(b)

Figure1 (a) Original Image with reflection, (b) Hard thresholding applied on image

(a)



(b)

Figure2 (a) Original Image with reflection, (b) soft thresholding applied on image

Resultant images obtained by proposed algorithm using hard as well as soft thresholding with different interpolation methods such as cubic, linear, spline and nearest. The corresponding results are shown in table 1, table 2, table 3 and table 4 respectively.

TABLE 1: Results for cubic interpolation

Parameter	Hard Thresholding	Soft Thresholding
MSE	445.44	551.26
PSNR	21.29	20.33
SSIM	0.7857	0.8392
Correlation	o.8573	0.7476

TABLE 2: Results for linear interpolation

Parameter	Hard Thresholding	Soft Thresholding
MSE	469.75	547.43
PSNR	20.88	20.36
SSIM	0.8469	0.7478
Correlation	0.7699	0.8401

TABLE 3: Results for spline interpolation

Parameter	Hard Thresholding	Soft Thresholding
MSE	445.97	551.61
PSNR	21.32	20.71
SSIM	0.7857	0.7531
Correlation	0.8572	0.3890

TABLE 4: Results for nearest interpolation

Parameter	Hard Thresholding	Soft Thresholding
MSE	515.93	608.75
PSNR	20.92	20.28
SSIM	0.7474	0.7990
Correlation	0.8118	0.7221

5. CONCLUSION

In this paper, we applied DWT and SWT to obtain super resolved image. The high frequency sub bands are interpolated with different interpolation techniques. We calculate the quality parameters of image such that MSE, PSNR, SSIM and correlation coefficient. In this experiment, we applied hard as well as soft thresholding on resultant image to reduce reflection in the image. Spline interpolation technique gives good PSNR while cubic interpolation gives good SSIM. The overall performance of the spline interpolation is comparatively good for hard thresholding operation for the resultant image.

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