
**International Journal of Control Theory and Applications**

ISSN : 0974-5572

© International Science Press

**Volume 10 • Number 4 • 2017**

# Super Resolution Technique for Reflection Reduction in Metal for manufacturing industries

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***Abstract:*** Quality inspection is very important in case of manufacturing industries. Quality inspection can be done manually. This manual inspection has many limitations. Manual inspection depends upon inspector's knowledge and patience. Hence it is risky process and generates number of errors. Hence for automation of inspection process, many industries are using image enhancement techniques. In quality inspection defect detection is performed when machine product is manufactured. Metal surface with high reflection coefficient, makes defect detection process more difficult. In image this reflection acts as noise. Edge detection cannot be performed easily because of this reflection in image. Hence reflection reduction is required to perform defect detection and edge detection. The aim of proposed method is to reduce reflection from metal body. Super resolution algorithm is used for reflection reduction. Hard and soft thresholding are performed using wavelet transform. These different algorithms are implemented on Raspberry Pi development board which will be suitable for manufacturing and automotive industries. This embedded system along with Raspberry Pi can be deployed in mechanical industries for quality inspection. Using parameters like MSE, PSNR quality evaluation is performed. Results obtained with MATLAB are compared with results with Raspberry Pi.

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

## I. INTRODUCTION

Every manufacturing industry requires quality inspection. It can be performed manually however knowledge and patience of inspector play important role in manual inspection. Therefore this process becomes inconsistent and inaccurate which may cause number of errors. To have better inspection many industries are now switching to automatic inspection. Image enhancement techniques can be used for automatic inspection. These techniques help in reducing errors and cost. Inspection method is used to check whether all requirements of product are fulfilled or not. Defect detection by manual inspection cannot give 100% results. To improve defect detection process automated inspection is required. It avoids problems arriving in next manufacturing phases due to faulty defect detection.

Metals like aluminum, gold, copper and silver etc. have high reflection coefficient. Currently, in many industries like automobile industries, domestic electronics, and communication and construction industries these metals are mainly used as raw material. Hence these metals should have good surface quality as quality of final product gets affected by them directly. Defect detection process becomes tedious in case of highly reflective metal. Inspection becomes complex in area which is affected by reflection. Light gets reflected from circular and straight edges and makes edge detection complex. Hence there is a requirement of designing a system which can perform reflection reduction and make inspection process easy [1].

Superresolution algorithm is one of the method used for reducing reflection from reflective metal. In proposed algorithm, wavelet transform is used to obtain superresolution. For reflection reduction, two types of wavelet thresholding can be used. Wavelet thresholding includes hard and soft thresholding. Image gets decomposed in to four sub bands after applying wavelet transform. It gives horizontal and vertical details in from of subbands (LL, LH, HL and HH). LL sub band gives approximation coefficients. LH sub band provides vertical details while HL gives horizontal details. Diagonal details are given by HH sub band. In this proposed work, first super resolution is performed and then reflection reduced image is obtained by applying hard and soft thresholding. These algorithms are implemented on MATLAB and Raspberry Pi and results are compared.

In this paper, section II describes previous work related to above topic. Proposed algorithm is described in section III. Section IV gives results and discussion and conclusion is given in section V.

## II. PREVIOUS WORK

Pedro de Almeida [2] has proposed method to reduce reflection which is present in color image. Reflection identification is done by two rules. Thresholding is done in first rule. Pixels having luminosity i.e. average RGB component values more than 250 are taken as reflections. In NICE. I images small and large white zones are present. Hence, there is a need of second rule. It is used to mark portions which are white as well as very small which represents the reflection. Then each reflected pixel gets replaced with average value of darker half of the pixels. These pixels are situated in restricted circle around the reflected pixel. The aim of this method is to improve iris and pupil location detection. Original information covered by reflections cannot be recovered by this method.

Dae Sik Jeong, Jae Won Hwang and Byung Jun Kang [3] has proposed a method to divide reflected image into two classes, good and bad detection. It uses corneal specular reflection (SR). In good detection, pupil and iris regions are detected correctly. However they are incorrectly detected in bad detection. Counting of SR points in pupil and iris region is done to obtain this classification. Generally, reflectance of corneal SR is more than others. Hence gray level of corneal SR is more than others. Therefore, SR points are nothing but pixels with gray level more than 250. If number of SR points is more than one it is good detection else it is bad detection.

AnisFarihan Mat Raffei[4] has proposed LIPSVM method i.e. Line Intensity Profile and a Support Vector Machine method. In this method, blue and green intensities are subtracted from higher intensity value i.e. 255. Pixel is said to be reflected if green and blue pixel intensities are less than red intensity of it. SVM is used for reflection classification. Afterwards, training and testing are performed. Reflected pixels are denoted by '1' while non reflected pixels are given by '-1'. Every reflected pixel is replaced by four nearby neighbors there in non reflected area.

Farmanullah Jan, Imran Usman and Shahrukh Agha [5] have proposed a method in which image is first converted into gray scale image. Then upper and lower gray level limits are found out. Threshold is calculated as T= (upper limit- lower limit-10). If gray value is less than T then pixel value is set to 1 otherwise set to zero to form binary image. Then complement of binary image is taken so that we get reflections as a white spots. Experimentally it is observed that area of white dots related to reflections is less than 80 pixels. Each pixel in reflected area is replaced by lower gray level value. Boundary artifacts are reduced by applying median filtering on image after reflection reduction.

Wojciech Sankowski et al [6], has proposed a method in which locations of reflections are detected first using reflections localization which gets followed by reflection filling in to remove the reflections. For reflection localization, gray scale image is obtained based on the luminance in-phase quadrature (YIQ) model in which threshold is calculated using maximum intensity in the image and average intensity of the image. Afterwards, localized reflections are filled using four neighboring non reflected pixels in the RGB image.

Tieniu Tan et al [7], have proposed method to remove specular reflections which act as brightest point in image of iris. In this method, binary reflection map is calculated using adaptive threshold. Bi-linear interpolation technique is used to fill the reflections.

Demiel-Anbarjafari [8], has proposed Super Resolution technique. In this method low resolution image is decomposed into different sub band images using stationary wavelet transform (SWT) and discrete wavelet transform (DWT). Bicubic interpolation is used for interpolation of high frequency sub bands. At the same time, interpolation of input image is done. Finally, inverse DWT (IDWT) is used to combine interpolated input image and interpolated high-frequency sub band. Finally super resolved image is obtained.

Xiaomin Wu et al [9] found the approximation sub bands of the HR image and the corresponding bicubic interpolated image are very similar but the respective detail sub bands are different. Therefore, an algorithm to learn four coupled principal component analysis (PCA) dictionaries to describe the relationship between the approximation sub band and the detail sub bands is proposed in their paper.

Zhang Liu We et al [10] has applied L0 image smoothing method to a given low-resolution image to get its low-resolution smoothing image which preserved sharp edges. Besides, a low-resolution error image was obtained by the difference between the low-resolution image and the low-resolution smoothing image.

Shao-Shuo Muet et al [11] proposes a multi frames upper resolution reconstruction based on self-learning methods. First, multiple images from the same scene are selected to be both input and training images, and larger-scale images, which are also involved in the training set, are constructed from the learning dictionary.

Chopade and Patil [12] proposed super-resolution technique in which dyadic-integer-coefficients based wavelet filter bank is designed. The proposed technique has integer and rational coefficients. It makes hardware implementation of this technique easy as computational complexity is low.

Gajjar and Joshi [13] presented a learning-based approach for super-resolving an image using single observation by the use of learning of high frequency sub-bands derived from discrete wavelet transform (DWT). In their work, orthogonal wavelet filter bank (db4) is used to extract the high frequency contents from the LR image. Jiji et al. [14] presented singe frame image super-resolution using wavelet coefficients than pixel values in different frequency sub-bands to determine high frequency components. Tsai and Haung [15] first introduced the frequency domain reconstruction super-resolution scheme where images are transformed into frequency domain by the use of Fourier transform (FT). Irani and Peleg [16] proposed the iterative algorithm that uses the current initial guess for super-resolved (SR) image to create LR images and then compare the simulated LR image with original LR image. Ji and Fermullar [17] proposed super-resolution reconstruction system by addressing the problem of frame alignment and image restoration based on standard bi-orthogonal wavelet filter bank (cdf-9/7). Nguyen and Milanfar [18] proposed wavelet-based interpolation-restoration method for super-resolution.

## III. PROPOSED SUPER RESOLUTION ALGORITHM

As per the discussion in section II, numerous different methods are available for reflection reduction from reflective metal. From all these methods, common procedure is followed for detection and reduction of reflection. These common steps are mentioned as follows: First i) reflection identification ii) reflection classification and iii) filling in reflections.

1. Identify the reflection: In this stage, RGB image is first converted into gray scale image having maximum intensity value of 255. It is observed that, when image of metal job is captured, light gets reflected from the surface of metal. Thus values of pixels get increased up to 255, where reflection is present. By observation, threshold value is settled on 200. As a result, pixels having intensity value greater than 200 are identified as reflected pixels.

2. Reflection classification: By observation, pixels having intensity less than 200 are classified as non reflected pixels whereas pixels having intensity greater than 200 are classified as reflected pixels.

3. Filling in reflections After reflection classification, reflections are removed by inserting nearby non reflected pixel values. Anis Farihan Mat Raffei [2] has proposed LIPSVM (Line Intensity Profile and a Support Vector Machine) method for RGB image to remove the reflections. In that method, he has used following formula to fill the reflections with adjacent non reflected color pixels.

$$\gamma_{fill} = \frac{\sum_{n=1}^{4} w_n \gamma_n}{\sum_{n=1}^{4} w_n} \tag{1}$$

Where,

$\gamma_n$ = color elements (R, G, B) of neighboring n$^{th}$ pixel

*Wn* = weight of pixel (inverse distance *dn*

In this method, each reflected pixel is interpolated by nearest non reflected pixel value. At the beginning of this stage, distance between reflected pixel and first identified non reflected one is calculated. Henceforth this determined distance (d) is kept constant. Now onwards, every identified reflected pixel gets interpolated by $d^{th}$ non reflected pixel. As a result reflection gets reduced. However image will be still affected by boundary artifacts. By applying median filtering these artifacts can be reduced. Resultant image is used for edge detection.

Super resolution is blend of low resolution images with blurred images of same scene. Single and multiple frame images can be used to achieve super resolution. In case of single frame super resolution, super resolved image is obtained using different interpolation methods. Here we have proposed super resolution algorithm for measurement of quality of images with reflection based on wavelet which uses different interpolation methods. Reflection reduction is achieved by applying wavelet thresholding that includes hard thresholding and soft thresholding. In this method, image of metal having high reflection is captured first. Captured image is then converted into gray scale one. Gray image is used for proposed method.

First image is decomposed into four sub bands LL1, HL1, LH1 and HH1 by applying Stationary Wavelet Transform (SWT) on image. The SWT differs from Direct Wavelet Transform (DWT) in terms of sub bands. In SWT, size of all four sub bands is equal to size of original image. DWT is applied on image after interpolating it by factor 2. DWT provides detail coefficients LH2, HL2 and HH2 with approximation coefficients LL2. Size of original image is four times more than size of each sub band. Now for achieving super resolution detail coefficients of both DWT and SWT are added and resultant coefficients (LH3, HL3, and HH3) are obtained. Approximation coefficients of DWT are now interpolated along with these resultant coefficients. Different interpolation techniques like linear, nearest, cubic, and spline are performed. Then IDWT is applied to get super resolved image. In the last part, wavelet thresholding i.e. hard and soft thresholding are applied. In this method, size of high frequency sub bands (1024×1024) is increased by using different interpolation techniques to get super resolved image of size 2048×2048. Above interpolation methods are used to check how high frequency components are preserved in image with super resolution.

Super resolution algorithm is used to enhance the details present in the captured image as mentioned below:

1. Capture image with reflection.
2. Stationary Wavelet Transform (SWT) is applied on captured image to get different sub bands.
3. Apply interpolation techniques like cubic, linear, nearest interpolation on captured image.
4. Direct Wavelet Transform (DWT) is applied on interpolated image to get different sub bands.
5. Add detail coefficients (HL, LH, and HH) of SWT and DWT respectively.
6. Apply interpolation techniques like cubic, linear, nearest interpolation on resultant detail coefficients obtained and approximation coefficients of DWT.
7. Apply Inverse Direct Wavelet Transform (IDWT).
8. Get super resolved image.

All above algorithms are implemented on credit card sized Raspberry Pi. In this paper, Raspberry Pi model B+ is used for implementation. It is developed by Raspberry Pi foundation in UK. It has ARM1176JZF-S 700 MHz processor. It has RAM of 512 MB. Raspberry Pi supports many programming languages like C, C++, Java, Python, and Perl etc. In this paper, Python programming language with OpenCV is used for real time implementation. OpenCV is an open source library of programming functions. OpenCV has libraries for image processing, communication, neural networks etc. It supports programming languages like C++, Perl, and Python with different operating systems like Linux, Android, and windows. Fig. 1 shows Raspberry Pi set up which is used for experimentation of proposed algorithm.

**Figure 1: Experimental set up for proposed algorithm**

**Hard Thresholding:** Hard thresholding represents 'keep or kill' operation. In hard thresholding, if threshold value is T then all pixel values less than threshold value T are made zero. Pixel values above threshold T are not altered. As it is hard thresholding, there are chances to loss of information. The following formula is used for hard thrshholding.

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

Where,

I = Pixel value

T = Threshold value

**Soft Thresholding:** Soft thresholding is operation where threshold value is flexible with respect to pixel value of image. The following formula is used for soft thrshholding.

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

Where,

I = Pixel value

T = Threshold value

Soft thresholding overcomes the drawback of hard thresholding. In soft thresholding, if the threshold value is T then all pixel values above threshold T are shrink by value T instead of making them zero.

## IV. RESULT AND DISCUSSION

For quality evaluation MSE and PSNR are used. MATLAB results and results obtained from Raspberry Pi are compared on the basis of MSE and PSNR.

1. Mean Square Error (MSE):

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

Where, Org (i, j) = Original image

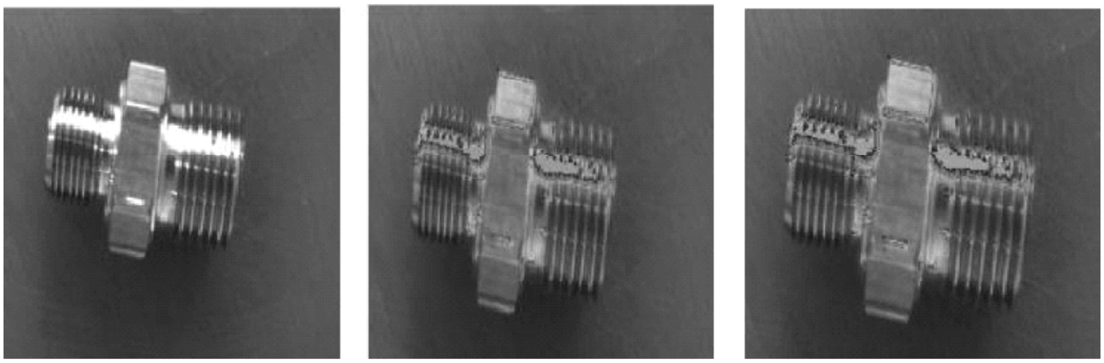
Rec (i, j) = Reconstructed image

In this parameter, reconstructed image is subtracted from original image to obtain an error. MSE is obtained by taking average of these errors.

2. Peak Signal to Noise Ratio (PSNR):

(a) (b) (c)

**Figure 2: Shows MATLAB results (a) Original Image with Reflection, (b) Hard Thresholding applied on image, (c) Soft Thresholding applied on image**



(a) (b) (c)

**Figure 3: Shows results obtained on Raspberry Pi (a) Original Image with Reflection, (b) Hard Thresholding applied on image, (c) Soft Thresholding applied on image**

**Table 1**
**MATLAB results for cubic interpolation**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 268.8524 | 261.6417 |
| PSNR | 22.5533 | 22.6714 |

**Table 2**
**MATLAB results for linear interpolation**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 276.7941 | 257.6417 |
| PSNR | 22.6269 | 22.7383 |

**Table 3**
**MATLAB results for nearest interpolation**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 314.6210 | 305.4481 |
| PSNR | 21.8706 | 22.9991 |

**Table 4**
**Results for cubic interpolation on Raspberry Pi**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 878.8121 | 882.5969 |
| PSNR | 18.6918 | 18.6726 |

**Table 5**
**Results for linear interpolation on Raspberry Pi**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 820.5037 | 825.5713 |
| PSNR | 18.99 | 18.9632 |

**Table 6**
**Results for nearest interpolation on Raspberry Pi**

| *Parameter* | *Hard Thresholding* | *Soft Thresholding* |
|---|---|---|
| MSE | 844.3334 | 847.8397 |
| PSNR | 18.8656 | 18.8472 |

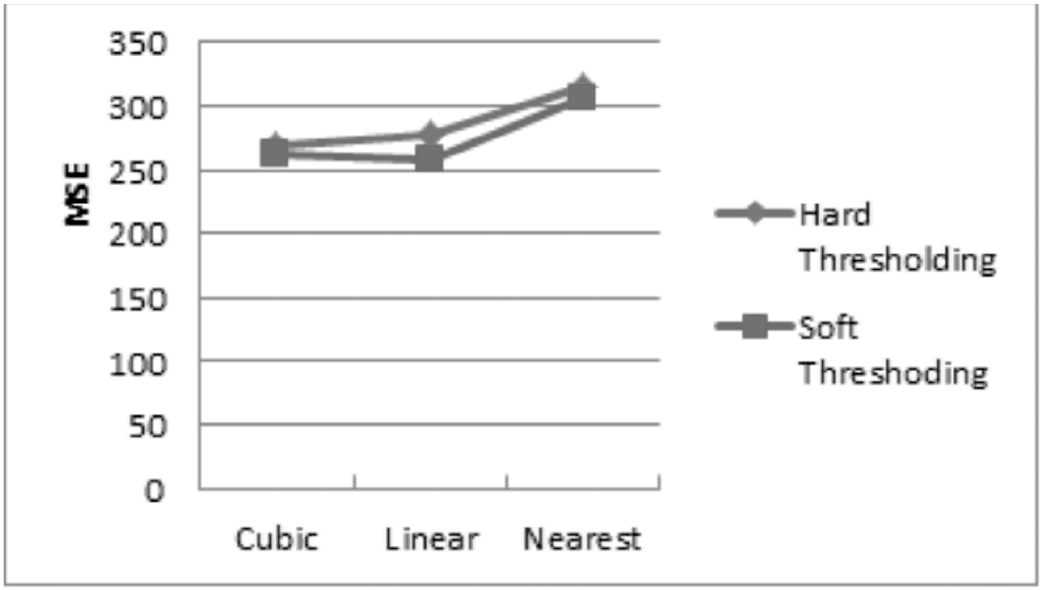



**Figure 4: Shows plot of interpolation technique vs. MSE for hard thresholding and soft thresholding using MATLAB**

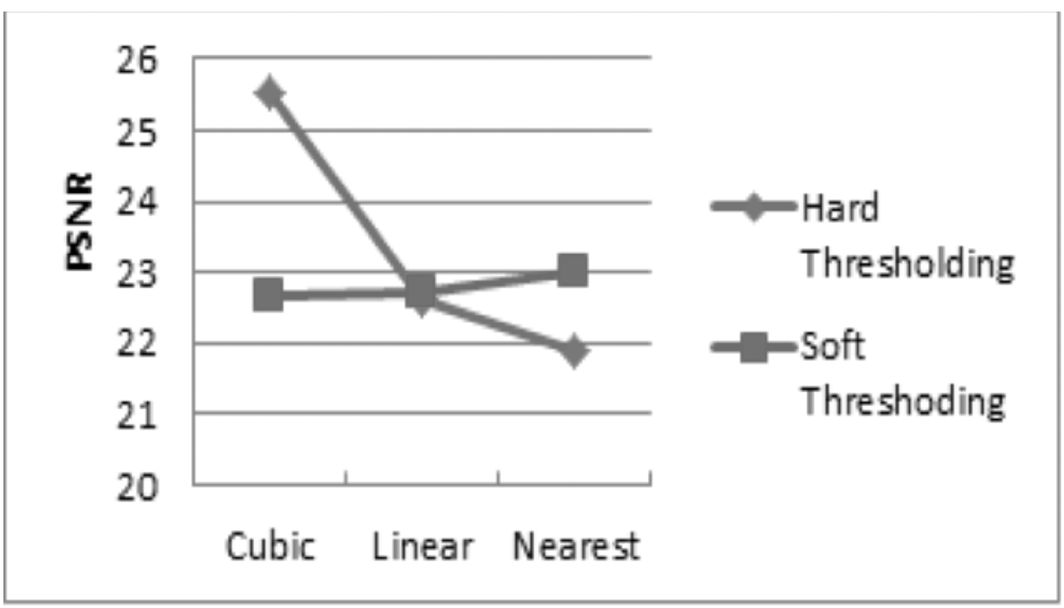



**Figure 5: Shows plot of interpolation technique vs. PSNR for hard thresholding and soft thresholding using MATLAB**

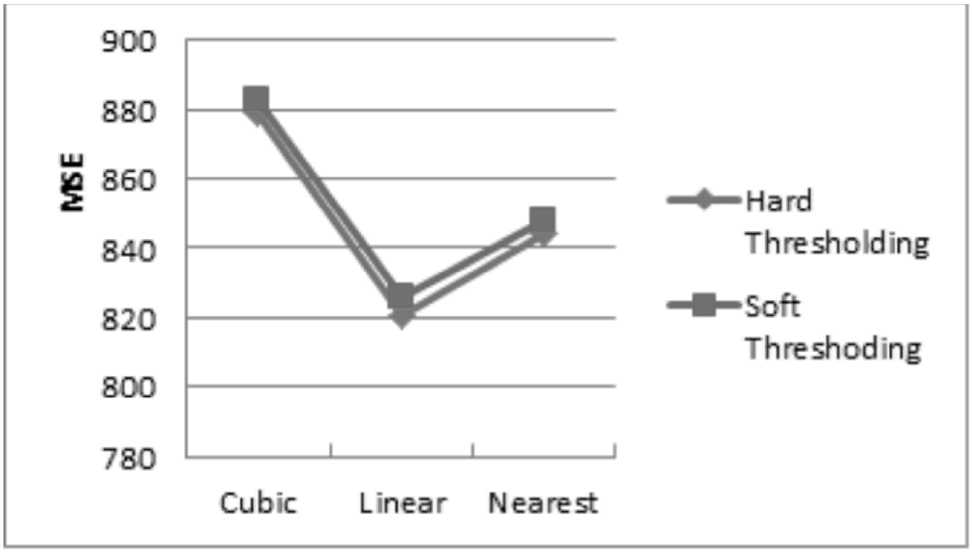



**Figure 6: Shows plot of interpolation technique vs. MSE for hard thresholding and soft thresholding on Raspberry Pi]**

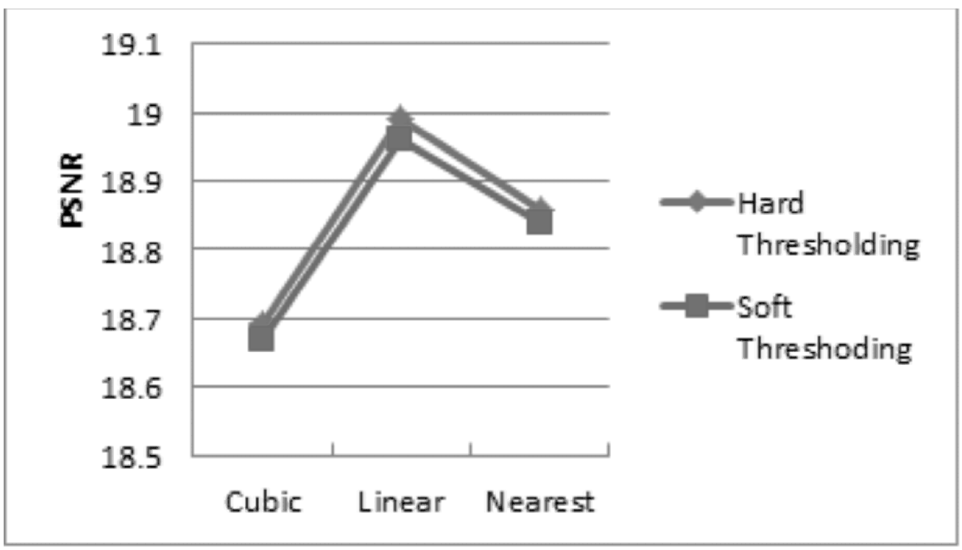



**Figure 7: Shows plot of interpolation technique vs. PSNR for hard thresholding and soft thresholding on Raspberry Pi**

Raspberry Pi is basically a mini PC, with an HDMI and analogue output. It can perform many common tasks which are generally performed by laptop or desktop. It supports real time operating system like Rasbian, Debian.The proposed algorithm has been developed in python environment, which is the default programming environment provided by Raspberry Pi.Though results obtained by Raspberry Pi development board are differing to some extent from the results obtained with MATLAB, Raspberry Pi is better for real time application as it is interactive with physical world.

Data shown in Table 3, is reflected in Fig.4 for cubic, linear and nearest interpolation techniques. It is evident from figure 4 that performance of soft thresholding is better for cubic interpolation. For data of Table 4, Table 5 and Table 6 are plotted in Fig.5, Fig.6 and Fig.7 respectively for MSE and PSNR with MATLAB and

Raspberry Pi.The result obtained for MSE and PSNR using MATLAB for different interpolation techniques is shown in Fig. 4 and Fig. 5. In the same style, the results for Raspberry Pi are shown in Fig. 6 and Fig. 7.It is observed that result obtained through Raspberry Pi can be correlated with real time values than the simulation software like MATLAB.

## V. CONCLUSION

In this proposed algorithm, linear, cubic and nearest interpolation techniques are used to obtain high resolution image. Hard and soft thresholdings are applied on super resolved image for reflection reduction. All these techniques are implemented on MATLAB simulation software and Raspberry Pi development board. In both cases MSE and PSNR parameters are calculated for highly reflective metals. Results obtained on Raspberry Pi are slightly deviating with results obtained on MATLAB software. Implementation on Raspberry Pi development board will be suitable for manufacturing and automotive industries. This embedded system along with Raspberry Pi can be deployed in mechanical industries for quality inspection.

## ACKNOWLEDGEMENT

The author Mr P B Chopade is working with MES's College of Engineering, Pune as an Associate Professor. We would like to thank institute for encouragement.

## REFERENCES

[1] Zhang Xue-wu, Ding Yan-qiong, Lv Yan-yun, Shi Ai-ye, and Liang Rui-yu, "A vision inspection system for the surface defects of strongly reflected metal based on multi-class SVM", *Expert Systems with Applications*,Vol.38, Issue 5, May 2011, Pages 5930–5939.

[2] Pedro de Almeida, "A knowledge-based approach to the iris segmentation problem", *Image and Vision Computing*,Vol.28, Issue 2, Feb. 2010, Pages 238-245.

[3] Dae Sik Jeong, Jae Won Hwang, Byung Jun Kang, Kang Ryoung Park, Chee Sun Won, Dong-Kwon Park and Jaihie Kim, "A new iris segmentation method for non-ideal iris images", *Image and Vision Computing*, Vol.28, Issue 2, Feb. 2010, Pages 238-245.

[4] Anis Farihan Mat Raffei, Hishammuddin Asmuni, Rohayanti Hassan and Razib M. Othman, "Fusing the line intensity profile and support vector machine for removing reflections in frontal RGB color eye images", *Information Sciences*,Vol.276, Auagust 2014, Pages 104-122.

[5] Farmanullah Jan, Imran Usman and Shahrukh Agha, "Iris localization in frontal eye images for less constrained iris recognition systems", *Digital Signal Processing*, Vol. 22, Pages 971-986, June 2012.

[6] Wojciech Sankowski et al, "Reliable algorithm for iris segmentation in eye image", *Image and Vision Computing*, Vol. 28, Pages 231–237, 2010.

[7] Tieniu Tan , Zhaofeng He, Zhenan Sun, "Efficient and robust segmentation of noisy iris images for non-cooperative iris recognition", *Image and Vision Computing*, Vol. 28,Pages 223–230, 2010.

[8] G. Anbarjafari and H. Demirel, "Image Super Resolution Based on Interpolation of Wavelet Domain High Frequency Sub-bands and the Spatial Domain Input Image", ETRI Journal, Vol. 32, No.3, pp. 390-394, June 2010.

[9] Xiaomin Wu, Jiulin Fan, Jian Xu and Yanzi Wang "Wavelet Domain Multidictionary Learning for Single Image Super-Resolution" *Journal of Electrical and Computer Engineering*, Vol, Article ID 526508,12 pages, 2015.

[10] Zhang Liu,Qi Huang, Jian Li and Qi Wang "Single Image Super_Resolution via L0 Image Smooting" *Mathematical Problems in Engineering*, Vol., Article ID 974509,8 pages, 2014.

[11] Shao-Shuo Mu,Ye Zhang,Ping Jia, Xun yang and Xiao-Feng "MultiframeSuperresolution Reconstruction Based On Self-Learning Method" *Mathematical Problems in Engineering* Vol., Article ID 181864, 12pages, 2015.

[12] P B Chopade and P M Patil, "Design of dydic-integer coefficient based bi_orthogonal wavelet filters for image super-resolution using image sub-pixel image" *ICTACTJournals*,vol. 04, Issue 04, May 2014.

[13] P. P. Gajjar and M. V. Joshi , "New-Learning Bases Super-resolution:Use of DWT and IGMRF Prior", *IEEE Transactions on Image Processing*, Vol. 15, No. 5, pp. 1201-1213, May 2010.

[14] C. V. Jiji, M. V. Joshi, and S. Chaudhari, "Single-frame image super-resolution using learned wavelet coefficients," *International Jornal Imaging System Technology*, Vol. 14, No. 3, pp. 105–112, 2004.

[15] R.Y. Tsai and T.S. Huang, "Multiple frame image restoration and registration," *Advances in Computer Vision and Image processing*, Vol., pp. 317-339, 1984.

[16] M. Irani and S. Peleg, "Motion analysis for image enhancement resolution, occlusion, and transparency," J. Visual Commun. Image Represent., vol. 4, pp. 324-335, Dec. 1993.

[17] H. Ji and C. Fermullar, "Robust wavelet-based Super-resolution Reconstruction", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, No.4, pp. 649-660, April 2009.

[18] N. Nguyen and N.P. Milanfar, "A Wavelet-Based Interpolation-Restoration Method for Super-resolution," Circuits, Systems, and Signal Processing, vol. 19, pp. 321-338, 2000.