A No Reference Image Blur Detection using CPBD Metric and Deblurring of Gaussian Blurred Images using Lucy-Richardson Algorithm

Suresh S. Zadage, G. U. Kharat

Abstract— This paper addresses sharpness of a no-reference image based on Cumulative Probability of Blur Detection (CPBD) metric and also deals with removal of this blur. CPBD considers prediction of human blur at different contrasts. The probabilistic model that calculates probability of blur detection at edges in the image are taken into consideration by CPBD [1]. This data is then spread over the entire image by calculating CPBD. The CPBD is tested by comparing it with different sharpness metrics for LIVE database images. Then the process of blur removal is done by reading the Gaussian blur image from LIVE database. The standard deviation for the test image is calculated while computing CPBD. Adjustment of standard deviation is followed by estimation of point spread function (PSF) and finally deconvlucy function is used to restore the image using Lucy-Richardson algorithm of deblurring.

Keywords— No reference, Image Quality, Gaussian blur, blurred image, deblurring, deconvlucy, Point Spread Function (PSF).

I. INTRODUCTION

In today's world, image quality is an important perspective of multimedia products as well as multimedia applications. Many industries and researchers are interested in objective image quality assessment. No-reference image quality assessment technique [1] has more importance as compared to full reference and reduced reference as it does not need any reference information. Blurring occurs due to loss of high frequency information during acquisition, processing and compression. Many sharpness metrics were developed which includes Just Noticeable Blur (JNB) [6], Local Phase Coherence (LPC) [9] etc. But none of these metrics were able to give a targeted performance. The sharpness metric based on a CPBD shows significant improvement in performance for images with both uniform and non-uniform saliency content.

In this work, we proposed improved no-reference blur detection metric which is a combination of both Just Noticeable Blur (JNB) and CPBD [1]. Also this paper deals with deblurring of a Gaussian blur image using Lucy-Richardson method. Basically Blur is nothing but image area without sharpness resulted by camera or movement of subject, inaccurate focusing. Blurring also caused by out of focus optics, use of wide angle lens, atmospheric turbulence or a short exposure time which reduces the number of photons captured.

Blurring effects consists of three blurring types:

1. Average blur: It is used when noise is present over the entire image. It is a tool to remove noise in an image. It can be distributed in vertical as well as horizontal direction. Also it can be circular averaging using expression, $R = (h^2+v^2)^{1/2}$, where R is the radius, h is horizontal size blurring direction and v is vertical size blurring direction.
2. Gaussian blur: In this blur type, pixel weights are unequal. The blur is high at the center and decreased at the edges following bell shaped curve. If we want to control blur effect, we have to add Gaussian blur to an image. Gaussian blur depends on the size and Alfa.
3. Motion blur: It makes image behaves like moving, when blur is added in specific direction. By angle 10 to 360 degrees this motion can be controlled. Also by intensity in pixels (0 to 999), this motion can be controlled depending on software used.

A blurred image is described by equation, $g = Hf + n$. Where g is blurred image, h is Distortion operator or Point Spread Function (PSF) [2], f is the original true image and n is the additive noise added during acquisition of an image that corrupts an image. The point spread function (PSF) represents degree to which an optical system blurs (spreads) a point of light. PSF is the inverse Fourier transform of optical transfer function (OTF). When PSF is convolved with an image, it creates the distortion. The deblurring is nothing but the deconvolution of the blurred image with PSF.

There are four methods of deblurring:

1. Deblurring with wiener filter: The *deconvwnr* function implements a least squares solution. Wiener deconvolution can be used effectively when the frequency characteristics of the image and additive noise are known to at least some degree.
2. Deblurring with a regularized filter: It uses the *deconvreg* function to deblur an image using a regularized filter. A regularized filter can be used effectively when limited information is known about the additive noise.
3. Deblurring with blind deconvolution algorithm: It uses *deconvblind* function to deblur an image.

Manuscript Received on August 2014.
Mr. Suresh Zadage, Department of ENTC, SPCOE, University of Pune, India.
Prof. Dr. G.U.Kharat, Principal, SPCOE, University of Pune. Pune, India.

The blind deconvolution algorithm can be used effectively when no information about the distortion (blurring and noise) is known.

4. Deblurring with the Lucy-Richardson algorithm: It uses the *deconvlucy* function to deblur an image using the accelerated, damped Lucy-Richardson algorithm. This function can be effective when you know the PSF but know little about the additive noise in the image

This paper is presented in five different sections: section II shows the proposed Cumulative Probability of Blur Detection (CPBD) metric. Deblurring of Gaussian blur image using Lucy-Richardson algorithm presented in section III. Section IV presents the performance results. A conclusion is given in section V.

II. CUMULATIVE PROBABILITY OF BLUR DETECTION METRIC

The performance of the CPBD sharpness metric is proposed based on the Just Noticeable Blur (JNB) [7]. As given in the section IV, CPBD gives consistently better performance across Gaussian blur type and across LIVE database when compared with earlier blur detection types.

As explained in [2], for given contrast C, The blur detection probability P_{BLUR} at an edge takes form of psychometric function given by,

$$P_{BLUR} = P_{BLUR}(ei) = 1-\exp(-|W(e_i)/W_{JNB}(e_i)|^{\beta}) \quad \ldots\ldots\ldots (1)$$

Where $W(e_i)$ is the measured width of the edge e_i, $W_{JNB}(e_i)$ is the JNB width. The JNB width depends on contrast 'C' in the adjustment of edge e_i. The value of β shows least squares fitting. The JNB width W_{JNB} is shown as equation [2]:

$$W_{JNB} = 5, \text{ if } C \leq 50 \qquad = 3, \text{ if } C \geq 51 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Equation (2) will calculates JNB width W_{JNB} depending on contrast value C.

If contrast is greater than 50 then W_{JNB} is taken as 3 or it is taken as 5[6]. If edge width=JNB width, then $P_{BLUR} = P_{JNB} = 63\%$.

The block diagram giving computation of CPBD metric is shown in fig 1. Firstly edge detection is done on the image. Here only horizontal edges are considered, because results have shown that including both horizontal and vertical edges does not results into any significant improvement. The image is divided into 64×64 blocks. By considering edge information in each block , the block is then divided into categories: edge and non-edge block. Criteria for deciding whether the block is edge block is as follows: The number of edges in each block is 0.2% of total number of pixels in that block. If it is not so, then that block is categorized as non-edge block and no further processing is on that block. For each edge pixel corresponding edge width is computed [6]. The JNB edge width is obtained based on the local contrast using equation (2). Then by using equation (1) the probability of blur detection at each edge pixel is calculated. If width of edge pixel and JNB width of that edge are equal then probability of blur detection is $P_{BLUR} = P_{JNB} = 63\%$.It is found that blur is not detected if $P_{BLUR} \leq P_{JNB}$. The probabilistic model is developed which gives Probability Density Function (PDF) of P_{BLUR}. At the end from the probability density function of P_{BLUR}, CPBD is computed as,

$$CPBD = P(P_{BLUR} \leq P_{JNB}) = \sum_{P_{BLUR}=0}^{P_{BLUR}=P_{JNB}} P(P_{BLUR}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where, $P(P_{BLUR})$ is probability distribution function at a given P_{BLUR}. This CPBD metric depends on the concept that at JNB, $W(e_i) = W_{JNB}(e_i)$ which indicates $P_{BLUR} = P_{JNB} = 63\%$.

The higher value of $W(e_i)$ edge width means image is highly blurred that is spreading at the edge is higher and hence a highest probability of blur detection at that edge. As discussed, mentioned CPBD metric (3), is related to percentage of edges at which $P_{BLUR} < P_{JNB}$ i.e. to percentage of edges at which blur cannot be detected. So, higher CPBD value shows sharper image regions.

III. DEBLURRING OF A GAUSSIAN BLURRED IMAGE USING LUCY-RICHARDSON ALGORITHM

It can be used effectively when point spread function (PSF) which is the blurring operator is known, but a little or no information is available for noise. The blurred and noisy image is restored by the iterative, accelerated, damped Lucy-Richardson algorithm. The additional optical system (e.g. Camera) characteristics can be used as input parameters to improve the quality of image restoration.

The *deconvlucy* function provides four adaptations:
1.Decreasing the effect of noise amplification: If we try to fit data closely, the problem of noise amplification occurs. After iterations, the restored image may look faulty and does not show the real structure of the image but show its adverse effect. The *deconvlucy* function uses DAMPAR parameter to control noise amplification. It specifies threshold level for deviation of the output image from original below which damping occurs. Damping also reduces ringing.
2. Overcoming Non-uniform image quality: Restoring of the image also leads to bad quality of receiving pixels as they vary with time and position. By using *deconvlucy* function with specified WEIGHT array parameter that certain pixels can be ignored assigning them a weight of zero in the WEIGHT array.
3. Controlling camera read out noise: Noise in CCD detectors is due to the photons counting noise with a Poisson distribution and read out noise with a Gaussian distribution. The Lucy-Richardson method solves the problem of first type of noise. The *deconvlucy* function with readout parameter controls camera read out noise. This parameter specifies an offset value that ensures that all values are positive.
4. Handling under sampled images: The *deconvlucy* function with SUBSMPL parameter gives sub sampling rate if data is under sampled. PSF at each pixel rate acts as finer grid PSF if under sampled data is a result of camera pixel binning. Otherwise by observing sub pixel offsets PSF can be obtained.

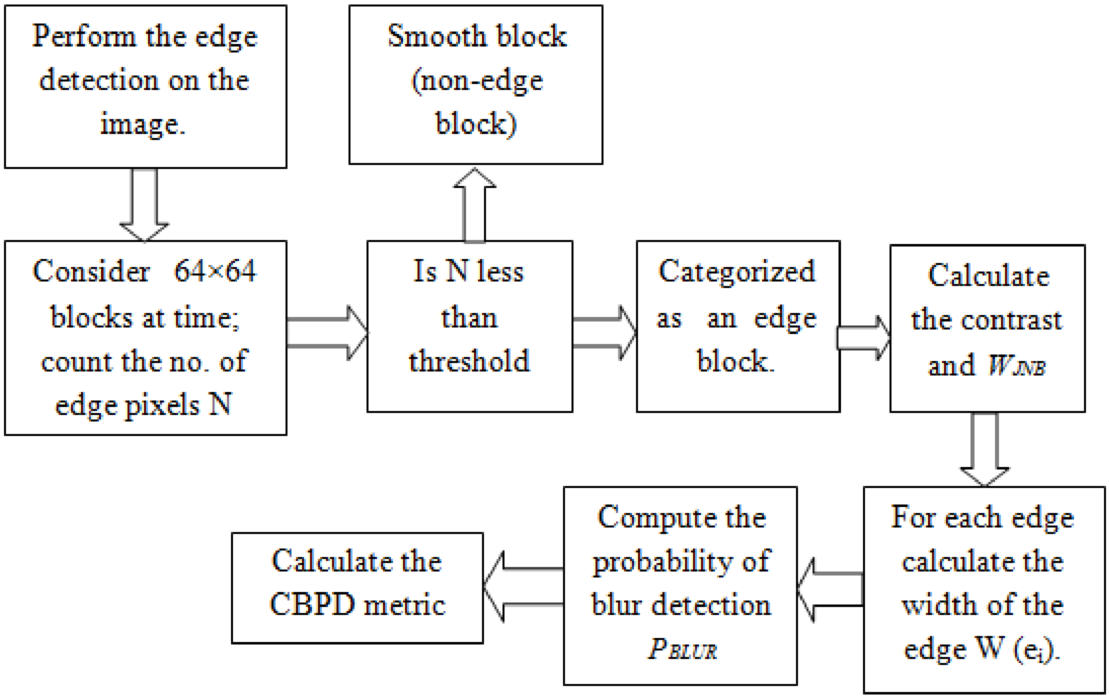


Fig. (1) Block Diagram Representing Evaluation of CPBD Metric.

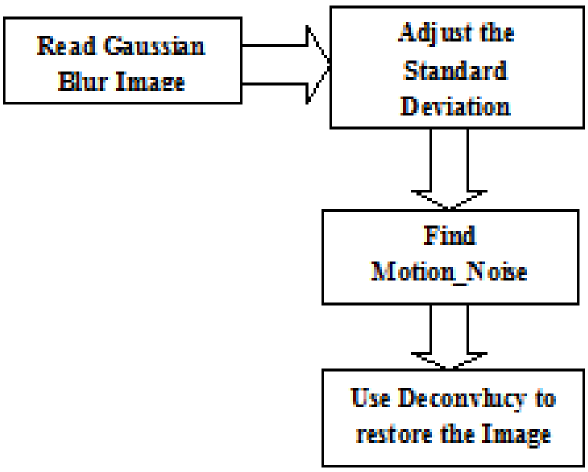


Fig. (2) Deblurring using Lucy-Richardson Method

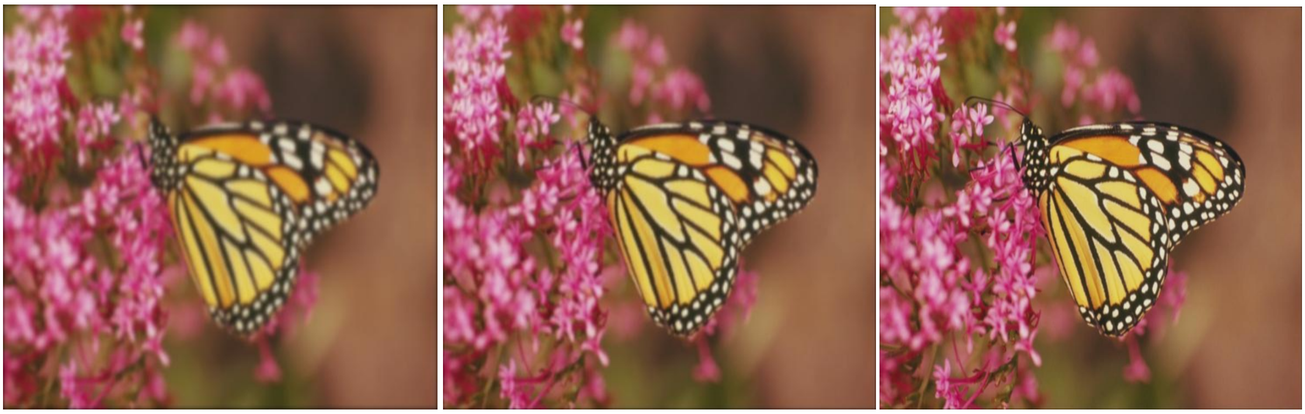
An image is read into the MATLAB workspace and following steps are performed:

1. I = imread('board.tif');
2. I = I(50+[1:256],2+[1:256],:);
3. figure, imshow(I)
4. title('Original Image')
5. PSF is created.
   PSF = fspecial('gaussian',5,5);
6. Simulated blur in an image is created and noise is added.
7. Blurred = imfilter(I,PSF,'symmetric','conv');
8. V = .002;
9. BlurredNoisy = imnoise(Blurred,'gaussian',0,V);
10. figure, imshow(BlurredNoisy)
11. title ('Blurred and Noisy Image')
12. The deconvlucy function is used to restore the blurred and noisy image, specifying the PSF used to create the blur, and limiting the number of iterations to 5 (the default is 10).
13. luc1 = deconvlucy(BlurredNoisy,PSF,5);
14. figure, imshow(luc1)
15. title('Restored Image')

IV. PERFORMANCE RESULTS

The resulting performance of CPBD metric is given in fig. (3). Fig. 3(a)-(c) shows the blurred versions of butterfly image. The blur in the image increases from Fig. 3(a)-(c). It is observed that if amount of blur increases the CPBD value decreases as shown in fig. 4 respectively. This is the condition for P ($P_{BLUR} \leq P_{JNB}$). The calculated P_{BLUR} values are rounded off using scalar quantizer with step size 0.01. These round off or quantized values calculates PDFs (P_{BLUR}) CPBD as in (3). The higher value of CPBD shows sharper image regions. So, as the blur in the image increases, the CPBD value should decrease.

Table I gives the results of CPBD metric as compared to JNB and LPC metrics for Gaussian blurred images. These images are obtained from the LIVE database. Fig. 5 shows the results of deblurring. If a real life image is taken then it is blurred by adding PSF and noise to it. Finally it is deblurred using *deconvlucy* function. In the above mentioned case we will get three figures: 1. Original image 2. Blurred image and 3. Restored image. As we are using Gaussian blurred images, there is no need to blur the images. So, we will get only two images: 1. Gaussian blurred image 2. Restored image Fig.5 (a) represents Gaussian blurred image of butterfly.
Fig.5 (b) shows restored image of butterfly using Lucy-Richardson algorithm.



(A) (B) (C)

Fig. 3(a)-(c): Shows distorted version of butterfly image having standard deviation of 0.3, 1.6and 2.7 respectively

TABLE I
COMPARISON OF CPBD VALUE WITH OTHER METRICS FOR LIVE DATABASE CEMETERY 627X482 SIZE IMAGES FOR GAUSSIAN BLURS DISTORTIONS

Metric	Image a	Image b	Image c
CPBD	0.6342	0.8942	0.9458
LPC	0.5985	0.8043	0.8923
JNB	0.5632	0.7725	0.8126

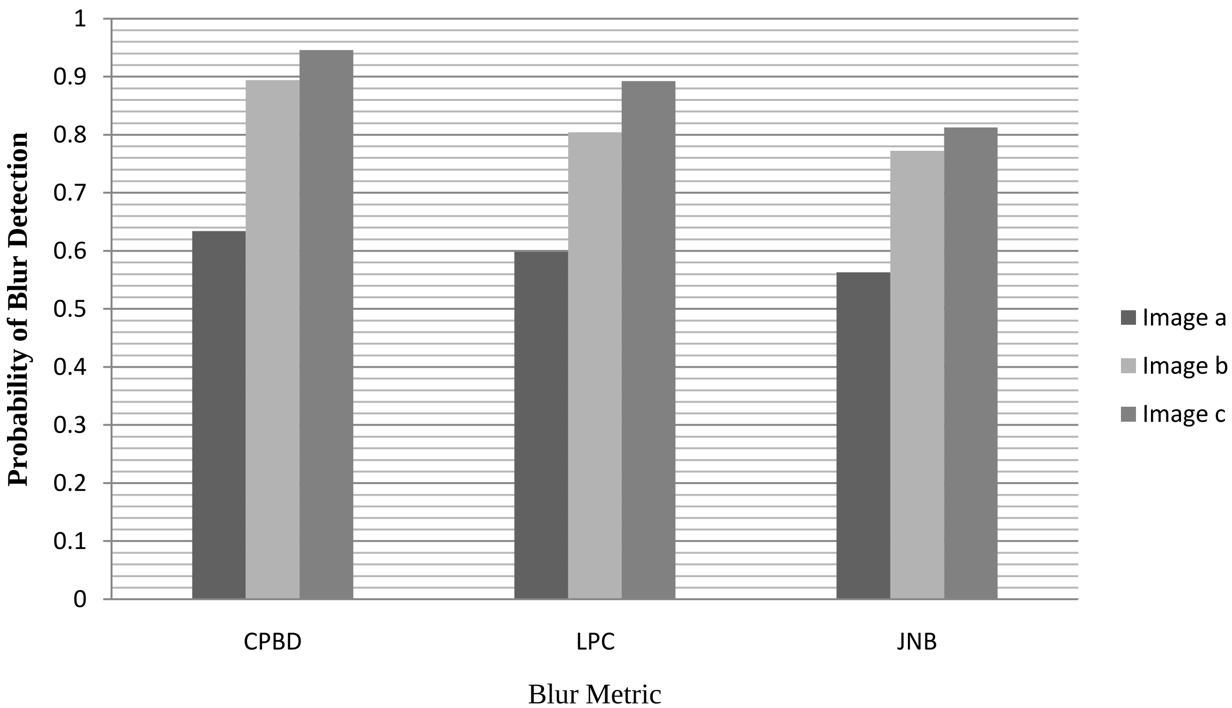
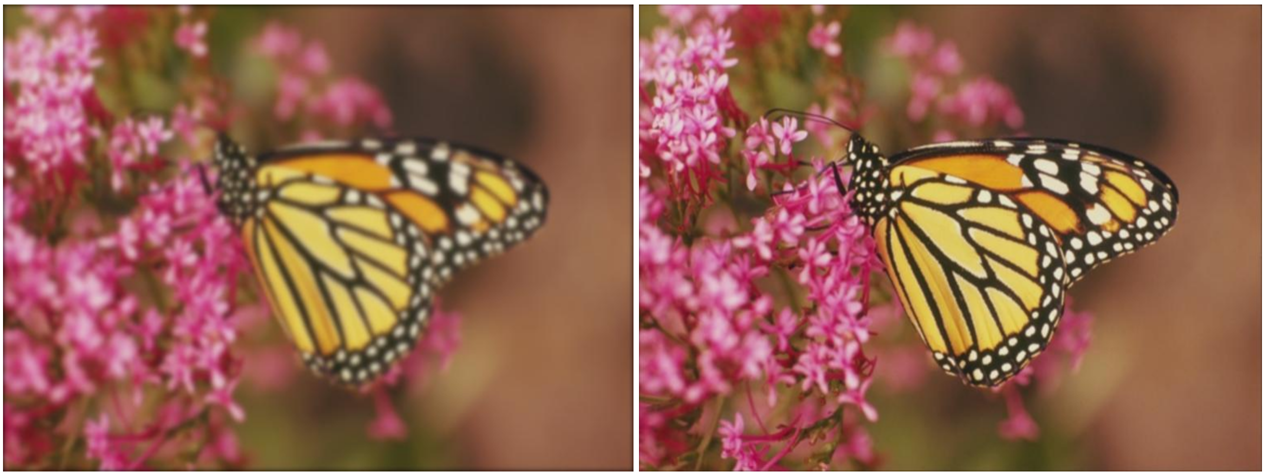


Fig. (4): shows comparison of different blur metrics for Gaussian blurs images shown in Fig. 3(a)-(c)



(A) **(B)**

Fig. 5 shows the results of deblurring. Fig. 5(a) represents Gaussian blurred image of butterfly. Fig. 5(b) shows restored image of butterfly using Lucy- Richardson algorithm.

IV. CONCLUSION

In this paper, blur detection metric CPBD is proposed. It is related to edge detection which follows computing of P_{BLUR} at detected edges. The PDF is computed to obtain probabilities from which final CPBD is calculated. The entire performance of CPBD metric is good for Gaussian blur images as compared to JNB and LPC metrics. The increased value of CPBD metric shows sharper image regions. The CPBD value is always between 0 to 1.0. This CPBD metric is useful in medical purpose like Telemedicine.

Deblurring study have shown that when amount of blur is known and noise is not added to the image , the regularized, wiener and blind techniques produces best results. But when Gaussian noise was added to the image in addition to blur, the
Lucy-Richardson algorithm actually produced the best results. When you know the exact PSF, the results of deblurring can be quite effective. So, Lucy-Richardson algorithms best suited when noise is presented with blur.

Research on this metric can be done in future considering blur detection in videos & 3-D contents by considering temporal and depth factors.

REFERENCES

1. Suresh S. Zadage and G.U.Kharat ."Blur Detection of a No Reference Image Using CPBD Metric", *IJMER*, vol. 3,issue 5(3). 2277-7881, May 2014.
2. Salem saleh al-amri, N.V Kalyankar ."Deblurred guassian blurred images", *Journal of computing*, vol. 2,issue 4.ISSn 2191-9617, 2012.
3. Niranjan D. Narvekar and Lina J. Karam ."No-reference Image Blur Metric Based on the Cumulative Probability of Blur Detection (CPBD)", *IEEE Trans. Image Process*., vol. 20, no. 9, pp. 2678-2683, Sep. 2011.
4. Rania Hassen, Zhou Wang and Magdy Salama, "No reference image sharpness assessment based on local phase coherence measurement", *IEEE international conference on acoustics,speech and signal processing (ICASSP10)*,Dallas,TX,MAR.2010.
5. R. Ferzli and L.J. Karam ," A no-reference objective image sharpness based on the notion of just noticeable blur (JNB)," *IEEE Trans. Image Process*., vol. 18, no. 4, pp. 717-728, Apr.2010.
6. N. D. Narvekar, and L. J. Karam, "A No-Reference Perceptual Quality Metric based on cumulative probability of blur detection," *First International Workshop on Quality of Multimedia Experience-09*, pp. 87-91, July 2009.
7. L.J. Karam, T. Ebrahimi, S.S. Hemami, T. N. Pappas, R. J. Safranek, Z. Wang and A.B. Waston ,"Introduction to the issue on visual media quality assessment," *IEEE Trans. Signal process.* , vol. 3, no. 2, pp. 189-192, Apr. 2009.
8. Niranjan D. Narvekar ," Objective no-reference visual blur assessment," *M.S. thesis Dept. Electrical Eng*., Arizona State Univ., Tempe, 2009
9. Z. Wang, G. Wu, H. R. Sheikh, E. P. Simoncelli, E. Yang, and A. C. Bovik, "Quality-aware images," *IEEE Trans. Image Process*., vol. 15, no. 6, pp. 1680–1689, Jun. 2006.
10. R. Ferzli and L. J. Karam, "No-reference objective wavelet based noise immune image sharpness metric," *IEEE international Conference on Image Processing*,vol. 1, pp. 405-408, Sept. 2005.
11. H. R. Sheikh, A. C. Bovik, and L. Cormack, "No-reference quality assessment using nature scene statistics: JPEG 2000," *IEEE Trans. Image Process*., vol. 14, no. 11, pp. 1918–1927, Nov. 2005.

AUTHORS PROFILE

Mr. Suresh Zadage, B.E. (E & TC), M.E.*, is studying in Sharadchandra Pawar College of Engineering, Dumbarwadi, (Pune). He has completed B.E.(E & TC) from SIT(University Of Pune) with distinction. His paper on **"**Blur Detection of a No Reference Image Using CPBD Metric" is published in International Journal IJMER. His area of research is Image Processing & enhancement.

Dr. G. U. Kharat, B.E., M.E., Ph.D**.** is working as Principal,Sharadchandra Pawar College of Engineering, Dumbarwadi, (Pune). He has 25 years of teaching experience as Professor, Associate Prof &Assistant Prof in engineering Colleges. More than 35 research papers in International journal/conferences are in his credit. His area of research is machine intelligence, Neural Networks and Artificial Intelligence.