View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by International Journal of Innovative Technology and Research (IJITR)

Analysis Of Moment Algorithms For Blurred Images

RUKSANA BEGUM
M.Tech (Digital System And Computer Electronics), SWCET, Khairthabad, Hyd.

S.VIJAYA BHARGAVI
Associate Professor, Dept. of ECE

G.ARUNA
Head Of The Department,Dept of ECE

Abstract-— **with the remarkable growth in image processing, the requirements for dealing out with blurred images is difficulty in a variety of image processing applications. In this paper presents the restoration of blurred images which gets degraded due to diverse atmospheric and environmental conditions, Blur is a key determinant in the sensitivity of image quality, so it is essential to restore the original image.The research outcomes exhibit the major identified bottleneck for restoration is to deal with the blurred images and also a set of attempts have been executed in image restoration using multiple moment algorithms. However the precise results are not been proposed and demonstrated in the comparable researches. Also detail understanding for applications of moment algorithms for image restoration and demonstrating most suitable moment method is current requirements for research. Hence in this work we employ most accepted moment algorithms to exhibit the effect of moments for image restoration and the performance of the moment algorithms such as the Hu, Zernike and Legendre moments is evaluated on image with different blurring lengths. Moreover the effect of moment algorithms is also demonstrated in order to find the optimal setting of orders for image restoration. The final outcome of this work is a stable version of MATLAB based application to visually demonstrate the performance difference of Hu, Zernike and Legendre moments. The relative performance of the application is also been demonstrated with the help of multiple image datasets of biometric identifier such as fingerprint, hand palm and human face.**

Index Terms— **Image Descriptors; Moment Algorithm; Image blurring; Zernike moment; Legendre Moment; Image Restoration;**

I. INTRODUCTION

Image processing is dynamic research area that has impact in several fields from remote sensing, traffic Surveillance, Biometric authentication system, robotics, to medicine. 3-D scene analysis and reconstruction are only a few objectives to deal with. Since the real sensing systems are sometimes lacking and also the environmental conditions are dynamic over time, the acquired images often. The image are the for the most part frequent component of information representation and transmission due to the robust nature of information storage and the continuous effort to make digital image processing and presentation better. The studies have shown that the images contain information which is redundant and changing a value may cause errors in the calculation for further steps. In the space of image processing, the restoration of images is the major expanse of research for many decades. Many researchers have proposed various algorithms and techniques for better restoration of images for various applications. However the collection of image is strongly dependent on the imaging agent. The quality of a image possibly will suffer from a variety of impairments, Still the key bottleneck for better restoration of images are the random distortion and blurring caused to the initial images to be provided as input to the recognition system [1] [2]. The distortion and blurriness of the images are not only dependent on the capture agent, but also depends on the environmental and human errors. The causes of blurriness are studies and classified in four major kinds. Firstly, the focal length of the capture devices, Secondly, during the capture of object in a time irrelevant scale needs to be mapped with the capture speed of the agent to avoid the blurriness [3]. Thirdly, sometimes due to environmental and human causes the stabilization of the capture devices may be disturbed causing the blurriness.

II. BASIC DEFINITIONS AND MATHEMATICAL BACKGROUND FOR MOMENT

In the broad-spectrum the relationship between the real image f(x,y), the acquired image g(x,y) and h(x,y) be Point spread function of the imaging system, the definition of image the linear convolution and this convolution equations is often used conciliation between universality and simplicity, it is universally adequate to represent many realistic circumstances such as motion blur of a flat scene in case of translational motion, out-of-focus blur of a flat scene, media turbulence blur and motion blur of a 3D.

In the broad-spectrum the relationship between the real image f(x,y), the acquired image g(x,y) and h(x,y) be Point spread function of the imaging system, the definition of image Blurring is represented as Eq.1 ,

III. IMAGE BLUR DETECTION

Before attempting to process the image for any useful information, it is critical to ascertain that the

 @ 2013-2017 http://www.ijitr.com All rights Reserved.

image being processed is of good quality. Among several quality attributes including blur, noise, contrast and saturation, image blur deteriorates high frequency contents in the image thereby making the image unworthy for any useful information retrieval. Incorporating image blur detection in a camera will help discard bad image data at the source itself. Image blur detection for general purpose images is a challenging problem. Two primary sources for blur are relative motion between the camera and the object and poor focus. The purpose of a blur detection system is to eliminate missed detections while achieving a low false alarm rate.

IV. BLUR PARAMETER ESTIMATION

After determining whether an image is blurred or not it is important to evaluate the image's Point Spread Function (PSF) to estimate the degree of degradation for further image restoration. Depending on the type of degradation, the blur may be parameterized differently. In the case of a motion blurred image this estimate gives the number of pixels in the blur and the blur direction.

V. ORGANIZATION OF THESIS

Section 1 presents a detailed literature review of the generalized problem of image quality detection, blur detection techniques and PSF estimation algorithms. Section 2 presents the details of implementation of three different blur detections algorithms, viz. Haar wavelet based blur detection (HAAR), modified blur detection using singular value decomposition (SVD), and intentional blurring pixel difference based blur detection (MOMENT). Results obtained on a comprehensive test on IR and MSI images are also tabulated in Section 2. In Section 3, point spread function estimation of motion blurred images using the auto-correlation method and Hough transform based methods were studied. The details of the respective algorithms are presented and tests were conducted by artificially blurring images by a given length in a given direction. Section 4 presents the conclusions and suggestions for future work.

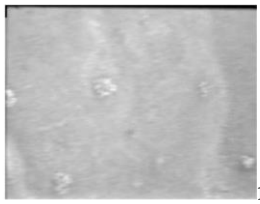
VI. APPROACH FOR BLURRED IMAGE RESTORATION USING MOMENT ALGORITHMS

Although Zernike and Legendre moments are useful methods for restoration of blur images, in this section, we discuss the presented approach for restoration using the following mathematical equations to express Zernike moments and Legendre moment. Thus the process of restoring the blurred image using Moment algorithm is presented in this frame work [Fig.1].

VII. IMAGE DEGRADATION PROCESS

In order to develop reliable blur detection it is important to understand the image degradation process. Degradation functions may be due to camera motion or defocus blur. Noise in the image is unavoidable as the sources of noise mostly stem from the imaging process itself and may be due to the imaging process (quantization effects), dark current, and others. For all practical purposes image noise is usually approximated to be white Gaussian.

The noise and degradation function have contradicting effects on the image spectrum. Noise often introduces additive broad band signals in the image data. Most degradation functions have the effect of averaging out the image data and act as a low pass filter.Blurring happens when each pixel in the image gets spread over the surrounding pixels. This spreading process is more often referred to as a smearing out around the neighboring pixels. Thus, the blurred image now has pixels that are affected due to this smearing process. An image blur is represented as a mathematical convolution between the source image and the point spread function which is known as the blurring kernel.Motion blur is caused by the relative motion between the object and the camera. The image so obtained contains an integration of pixel intensities that moved during the period of exposure governed by the camera's shutter speed. A motion blurred image is easily identifiable to human eyes because such an image will be clearly blurred or smeared in the direction of motion. The PSF estimation of the motion blurred image will help identify the number of pixels by which motion happened and the direction of the blur the figures are shown below.



f
ig:motion blurr image fig:defocus blurr image

VIII. WAVELET APPROACH TO BLUR DETECTION

The idea of using a wavelet transform approach for blur detection was published by Tong et al. in [7]. The fundamental principle behind this approach is examining the edge sharpness level to arrive at a decision. Wavelet theory has proved to be an excellent mathematical tool for the analysis of singularities like edges in images and subsequently for edge detection. The ability of the wavelet transform to characterize the local regularity functions is a very important property [20]. In [20], a relationship is obtained between the geometric properties of the edges and Lipschitz exponent in the form of equation.

(1) step structure edges with α=0 , (2) roof structure edges with α=1, and (3) dirac structure edges with α= -1. These three basic edges structures have been

 @ 2013-2017 http://www.ijitr.com All rights Reserved.

dealt with in detail with regard to Lipschitz exponent α and wavelet transform [7].

The Step-structure edges are further classified into Astep-structure and Gstep-structure edges based on whether change of pixel intensity is gradual or abrupt. A graphical description of different types of edges as mentioned in [7] is presented in below figures.

IX. HAAR WAVELET TRANSFORM

Let us consider a 1D image with just 4 pixels [9 7 3 5]. Now, the first low resolution image can be obtained by pair wise averaging giving [8 4]. There is a reduction of 50% image data as evident

from the fact that there are only two pixels instead of the original four pixels. Certainly there is loss of information. These two pixels so obtained are called the approximation coefficients of the original image. In order to recover the original four pixels, the detail coefficient needs to be stored in some form. The first detail coefficient is one so that seven is one more than the first approximation coefficient and one less than nine. Similarly, a second detail coefficient value of negative one leads to recovering the third and fourth pixel of the original image. Table 2.2 gives the detail and approximation coefficients for this example.

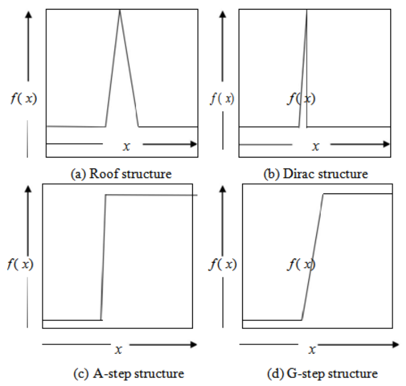
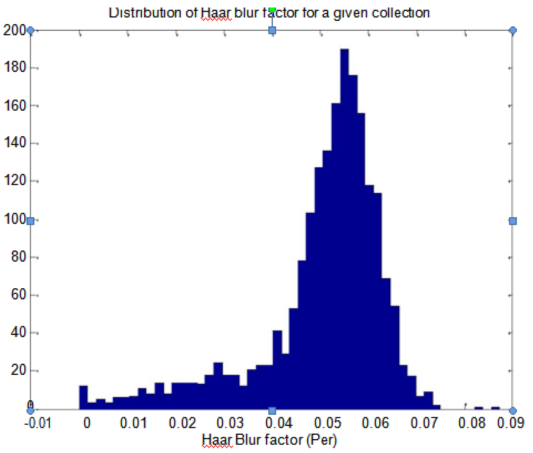


Figure 2.2 A defocus blurred image

X. HAAR WAVELET TRANSFORM

Let us consider a 1D image with just 4 pixels [9 7 3 5]. Now, the first low resolution image can be obtained by pair wise averaging giving [8 4]. There is a reduction of 50% image data as evident from the fact that there are only two pixels instead of the original four pixels. Certainly there is loss of information. These two pixels so obtained are called the approximation coefficients of the original image. In order to recover the original four pixels, the detail coefficient needs to be stored in some form. The first detail coefficient is one so that seven is one more than the first approximation coefficient and one less than nine. Similarly, a second detail coefficient value of negative one leads to recovering the third and fourth pixel of the original image. Table 2.2 gives the detail and approximation coefficients for this example.



XI. CONCLUSION

This thesis considers the problem of blur detection as a critical image quality metric. The problem of blur detection has been pursued by computer vision researchers for a very long time. The ability of a computer to detect between a good and bad image data is challenging task especially in time critical real time applications. The problem of automatic blur detection finds application in modern digital cameras that can detect for bad images and automatically discard them, time critical image inspection, biomedical applications in detecting images that even an experienced cardiologist will not be able to say whether an image is good or not. A large number of airborne images that was captured in 2009 suffered motion blur and some of them suffered defocus blur. Manual inspection of the massive data set consumed several man hours and hence an automatic detection for blur in these airborne images became inevitable.

XII. FUTURE WORK

Further work could be simultaneous decision based on detection and estimation and discarding the bad frames dynamically. Also, detection can be extended to give more specific details as to whether the image suffered a motion blur or defocus blur and accordingly carry out the estimation part.

XIII. ACKNOWLEDGMENT

I am very much thankful to the most respected Associate Prof. S.VIJAYA BHARGAVI, Electronics and communication SWCET, who at very discrete step in study of this subject, contributed His valuable guidance and helped to solve every problem that arise. I would like to extend my special thanks to Principal Dr. SUBBARAJ for spending his valuable time to go through my report and providing many helpful suggestions.

 @ 2013-2017 http://www.ijitr.com All rights Reserved.

XIV.REFERENCES

[1]. Ouni, S., Chamnah, M., Herbin, M., Zagrouba, E., "Are Existing Procedures Enough? Image and Video Quality Assessment: Review of Subjective and Objective Metrics," in proceedings of SPIE, Farnand, S.P., Gaykema, F., Image Quality and System Performance V, 6808, pp. 68080Q-1 – 68080Q-11, 2008.

[2]. Joshi, N., Szeliski, R., Kreigman, D.J., "PSF estimation using sharp edge prediction," in IEEE Conference on Computer Vision and Pattern Recognition, pp. 1-8, 2008.

[3]. Cohen, E,. Yitzhaky, Y., "No-Reference assessment of blur and noise impacts on image quality," published in Springer London, Signal, Image and Video Processing, 2009.

[4]. Marzialono, P., Dufaux, F., Winkler, S., Ebrahimi, T., "A no-reference perceptual blur metric," in proceedings of IEEE international conference on Image Processing, Vol. 3, pp. 57-60, 2002.

[5]. Marichal, X., Ma, W.Y., Zhang, H., "Blur determination in the compressed domain using DCT information," in proceedings of IEEE international conference on Image Processing, Vol. 2, pp. 386-390, 1999.

[6]. Chong, R.M., Tanaka, T., "Image extrema analysis and blur detection with identification," in proceedings of IEEE international conference on Signal Image Technology and Internet based systems, pp. 320-326, 2008.

[7]. Tong, H., Li, M., Zhang, H., Zhang, C., "Blur detection for digital images using wavelet transform," in proceedings of IEEE international conference on Multimedia and Expo, Vol. 1, pp. 17-20, 2004.

[8]. Andrews, H,C., Hunt, B.R., "Digital Image Restoration," Englewood Cliffs, NY, Prentice-Hall, 1997.

[9]. Savakis, A.E., Easton Jr, R.L., "Blur identification based on higher order spectral nulls," in proceedings of SPIE, Image Reconstruction and Restoration, Vol. 2302, 1994.

[10]. Pao, T.L., Kuo, M.D., "Estimation of the point spread function of a motion-blurred object from autocorrelation," in proceedings of SPIE, Lance T.Wu., Visual Communications and Image Processing conference., Vol. 2501., 1995.

[11]. Yitzhaky, Y., Kopeika, N.S., "Identification of Blur Parameters from Motion Blurred Images," in Graphical Models and Image Processing, Vol. 59, No. 5, pp. 310-320, 1997.

AUTHOR DETAILS

RUKSANA BEGUM received B.E in ECE from OU and currently pursuing M.Tech in DSCE at SWCET, Hyd.

S.VIJAYA BHARGAVI completed B.Tech in ECE received double M.Tech in DSCE and systen and signal procesing ,she is havingmore than 17 years of experience Currently working as Associate Professor at SWCET, Hyd.

 @ 2013-2017 http://www.ijitr.com All rights Reserved.