Comparison of two image-blur reduction techniques for images captured by smart phones

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Abstract*— Image blur is persistent in most images taken when a camera is hand-held. The blur may vary from being an acceptable bokeh to values that can ruin the photograph. This project simulates two image deblurring techniques that have been previously accomplished successfully and performs a comprehensive comparison of the result. In this project both subjective and objective methods have been used to evaluate the deblurred images. The first method[1] employs tonal correction using two images, viz. a blurred image and a low exposure image captured by the camera at high shutter speeds. Whereas, the second method[2] performs deblurring by a blind de-convolution of the blurred image with a point spread function generated using sensory data. In the end a third method is proposed that attempts to perform a fast and computationally economical solution.

Keywords: Image Deblurring, Hand-shake, Low Exposure, Point Spread function, Histogram matching.

I. INTRODUCTION

Computational photography refers to computational image capture, processing, and manipulation techniques that enhance or extend the capabilities of digital photography. It encompasses operations like panoramic addition of images, HDR photography, deblurring among others. Image deblurring is one of the fundamental operations that a consumer would want in latest cameras and smart phones. Although present devices have hardware facilities for vibration resistance, the blur caused by “hand shake” is often very difficult to remove and needs computational processing.

Various image debluring methods have been proposed to date, most of which can be divided into two broad categories: pre-processing and post processing. This project studies the effectiveness of one method from both groups.

The primary advantage of performing on-device image deblurring is that, one does not have to wait for the exact moment to click a picture. Most people handling cameras are novices and are not professionally trained to exploit the features of present day devices to their fullest advantage. Hence a feature of auto-deblur will be a boon for amateur photographers and camera users in general.

Some of the researches done recently in the image deblurring sector include:

- Image Deblurring via adaptive tonal correction.[1]
- Image Deblurring using inertial sensors.[2]
- Image Deblurring using adaptive learning. [3]
- Blind motion deblurring using sparse approximation.[4]
- Blind Image Restoration.[5]

In this project we study two image deblurring techniques and their effectiveness in performing the task at hand. In section 2 of this report we discuss the problem definition and its relevance in detail. Section 3 is a discussion of the two techniques. The apparatus and set up have been discussed in section 4. Section 5 introduces a proposal based on present learning. Section 6 contains objective and subjective results and analysis of advantages and short comings of the methods. Section 7 concludes the report followed by references.

II. PROBLEM DEFINITION

To implement pre-processing and post-processing algorithms to perform image deblurring, followed by qualitative and quantitative analysis of the results.

The essence of image deblurring lies in its visual appeal to the human eye. In that context, there may be scenarios where the deblurred image is statistically incoherent with the blurred image, however it might be visually pleasing; and vice versa. Hence it is important to perform extensive qualitative survey to map the visual results to the statistical observations.

The images used in the study are of varied color composition and are captured under different lighting compositions (both indoors and outdoors) to encompass a majority of scenarios where the algorithms might be subjected to work upon. This not only gives us a considerable database of images to work with, but also gives us an idea of how important task “data collection” is.

III. DEBLURRING TECHNIQUES

A. Image Deblurring using adaptive tonal correction (ATC).

The solution presented in [1] takes into consideration the constraints of the cell-phone platform. It utilizes only one image that is automatically captured at a low exposure setting immediately after an image is taken. Due to the lower exposure time, the blur is often removed or significantly reduced. However, the blur free image is dark due to the short exposure time. This algorithm emphasizes on mimicking the statistics of the original blurred image onto the low exposure image by performing an adaptive tonal correction. This approach is highly suitable to be deployed on a cell phone platform considering its high computational efficiency. Also, there are no assumptions made regarding the hand shake motion.

Following two equations govern the ATC process:

$$f(x) = \frac{\log(\,\alpha x - x + 1\,)}{\log(\,\alpha\,)} \;\cdots\; (1)$$

$$g(x) = \frac{\tan^{-1}(\beta \times f(x) - 0.5)}{\{\,2 \times \tan^{-1}\left(\frac{\beta}{2}\right)\} + 0.5} \;\cdots\; (2)$$

Eq. 1 and Eq. 2 represent tonal correction in the mean and variance respectively. The range of α used for the algorithm is 1 – 80 and that for β is 1 – 20 in increments of 1.

To facilitate functions like logarithm and arctan in MATLAB®, the images are converted to a double format. To perform tonal corrections on a color image, the images are converted to the *HSI* color space and operated upon the 'v' parameter. It is then converted back to RGB, using the original hue and saturation parameters.

B. Image Deblurring using inertial measurement sensors.

This approach has been adopted in [2], where a PSF mask is obtained using the data derived from inertial sensors. Since direct access to the inertial sensors in the image capturing camera is not available, an apparatus was designed to use the data from an iOS® application: Pocket IMU.

This app provides the accelerometer and gyroscopic data, of which acceleration data was used to estimate the PSF for deblurring.

The following assumptions were made in deblurring images using this algorithm:

- Ratio of the focal length 'f' of the camera and distance from the subject, 'z' is a constant.
- There is motion only in x and y directions, and the distance of the camera from the subject is a constant.

The projection of a point onto the image is thus given by:

$$C(\tau) = \begin{bmatrix} x' \\ y' \end{bmatrix} + f \begin{bmatrix} \emptyset x(\tau) \\ \emptyset y(\tau) \end{bmatrix} \;\cdots\; (3)$$

Where $\emptyset x(\tau)$ and $\emptyset y(\tau)$ are the position vectors in x and y directions, obtained by double integration of the acceleration vectors obtained from the inertial sensors. And *x'* and *y'* are positions of a point in an image. However since we are assuming the beginning of the image at the top left corner, i.e. pixel *(0, 0)*, *x'* and *y'* become zero. Thus, the final governing equation remains:

$$C(\tau) = f \begin{bmatrix} \emptyset x(\tau) \\ \emptyset y(\tau) \end{bmatrix} \;\cdots\; (4)$$

Where, $C(\tau)$ is the final PSF mask. This mask is used to obtain the deblurred image using a blind wiener deconvolution with the blurred image as described by Eq. 5

$$U = G \frac{H^*}{|H|^2 \;+\; \emptyset} \;\cdots\; (5)$$

Where, U, G and H are the Fourier transforms the deblurred image *u*; observed image *g*; and the PSF h and $\emptyset$ is the estimated inverse SNR.

To make the deblurring faster, the operations are performed on the intensity plane of the image after it is converted to the HSI space. Also, since the programming is done in MATLAB®, to facilitate calculus functions, the images are converted to a double format.

The pseudo algorithms used to accomplish the methods discussed above are placed towards the end of the report.

IV. APARATUS FOR CAPTURING IMAGES

A. Digital SLR Camera

A Nikon® D3100 was used to capture the both blurred and low exposure images. The advantage of using one is that we can obtain a "truly" low exposure image by controlling the shutter speed and not lowering the same digitally as done in camera phones. This makes sure that the captured image is of the best possible quality despite being a dark one.

A DSLR also allows one to fix the ISO, aperture, and focal length as compared to point and shoot cameras. This makes the blurred and low exposure images to differ only in the tonality and not in other image parameters.

B. Smart Phone

An Apple® iPhone was used to obtain the inertial data required for approach discussed in section 3B.

The latest phone helps measure precise data making simulation of the process as accurate as possible.

C. Set up

To capture the data and the images at the same time, the iPhone was strapped to the wrist using an iPhone wrist band accessory. This makes the motion in the image and the sensors as near as possible leading to accurate simulation.

V. PROPOSED METHOD

Here we propose a method which is divided into two phases: brightness quotient correction and contrast quotient correction. This method performs linear mapping for the brightness quotient. Hence reducing the time of operation and increases the range of output intensities to a greater extent. The second phase (contrast quotient correction) works on the lines of Adaptive Tonal Correction.

The first phase has been implemented and the results are tabulated below along with other results. Although partial correction has been applied, the statistical and visual data prove that the correction is at par with the ATC method. Hence it provides an even faster method of deblurring an image on a device.

Moreover since the operations are liner, matrix operations can be performed which increase both the efficiency and accuracy of the process.

VI. RESULTS AND ANALYSIS

As cited above, the algorithms discussed in section 3 were applied on 50 images and the collected data has been presented in the compact disk submitted along with the report.

A survey was conducted via email and Google Docs® to collect subjective data on the images processed by the two algorithms and the third proposed algorithm. The conclusion from this survey was then compared with the results obtained from objective analysis. The results from the survey and objective analysis have been illustrated below.

As is evident from the graphs, the results from ATC correction are better than those of the PSF Correction model

VII. CONCLUSION

As evident from the graphs and images shown below, in the current scenario, ATC fares much better than inertial mapping of PSF. This inference can be attributed to the following reasons:

- ATC performs mimicking of blurred image statistics onto the low exposure image.
- This in turn results in an image that is not distorted.
- Also, since no assumptions are made about the hand shake, the yielded output is free of other calculative errors.
- The PSF method assumes zero motion in the direction towards the subject.
- Moreover, since actual inertial data is not available, the results obtained are far from expected.
- In cases where the data is sufficiently large and precise, good results are obtained. Although those are a rarity.

REFERENCES

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[2] Image Debluring in Smart Phone Devices using built-in inertial measurement sensors.

[3] Single Image Deblurring with Adaptive Dictionary Learning.

[4] Blind motion deblurring from a single image using sparse approximation.

[5] Quality Measures for Blind Image Deblurring.

RESULTS

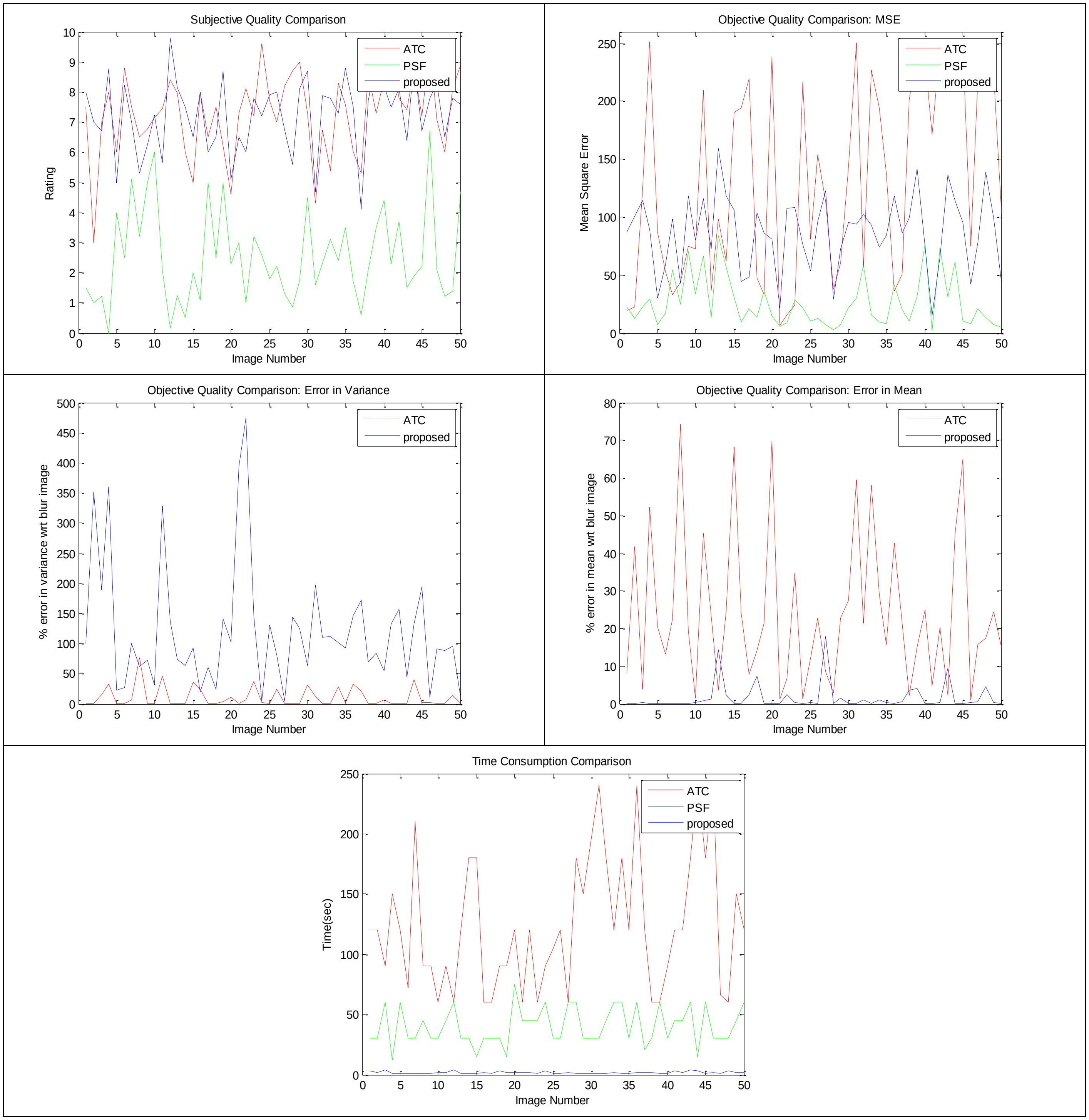

Fig. 1: Objective and Subjective Statistics of the three methods.

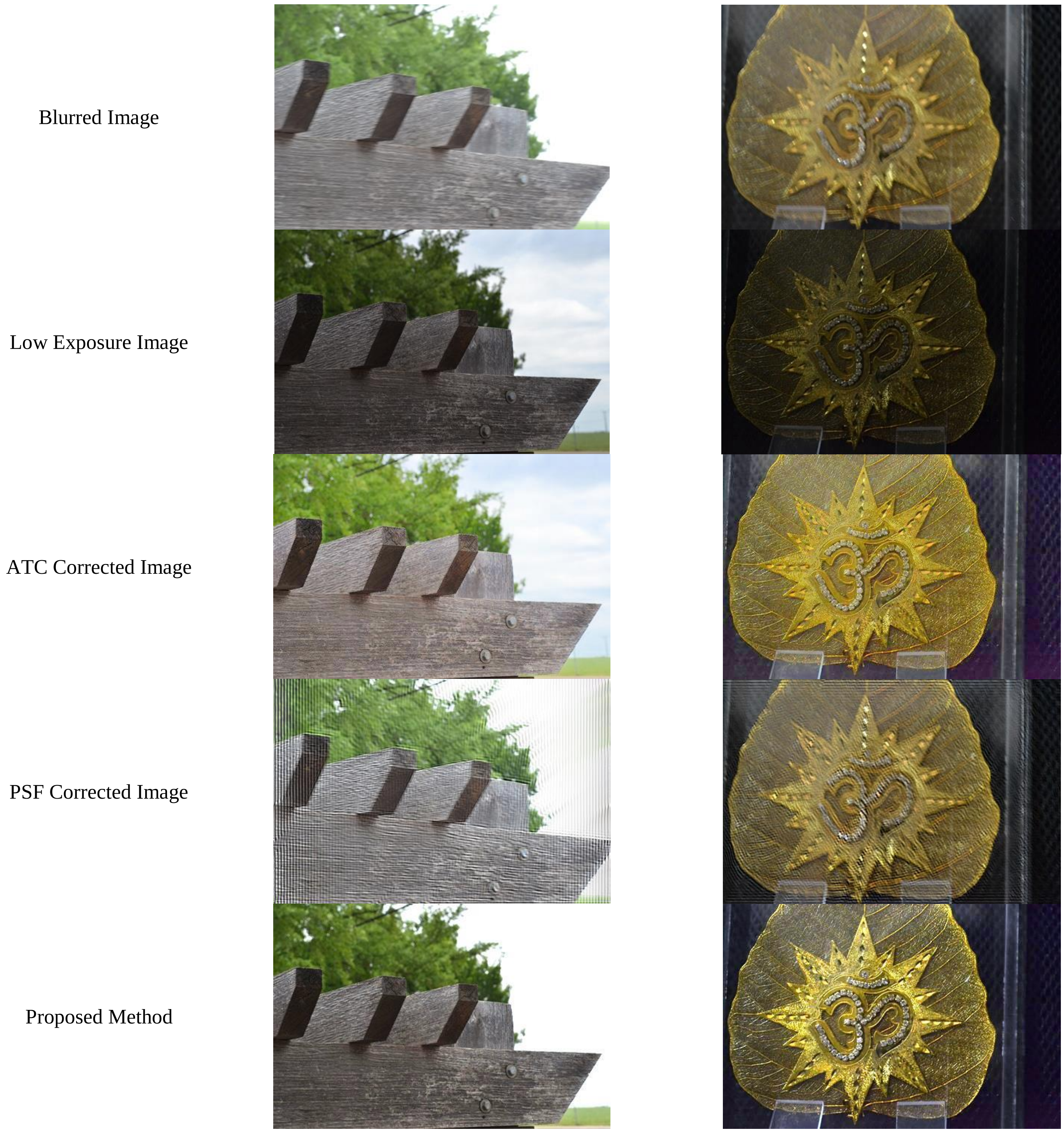

Fig. 2 a, b: Two sample images and their respective deblurred outputs.

Blurred Image

Low Exposure Image

ATC Corrected Image

PSF Corrected Image

Proposed Method

Fig. 2 c, d: Two sample images and their respective deblurred outputs.