# IMAEG BLUR REDUCTION FOR CELL-PHONE CAMERAS VIA ADAPTIVE TONAL CORRECTION

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### ABSTRACT

Image blur occurs often when using a cell- phone camera due to handshakes or jitter. Although there exist many motion deblurring algorithms in the literature, the computational complexities of these algorithms and the assumptions considered make them unsuitable for deployment on a cell-phone camera processor. This paper presents an image blur reduction algorithm for cell-phone cameras having a low computational complexity and without making any assumption about the handshake motion. This algorithm utilizes one low-exposure image in addition to a blurred image to perform a blur reduction operation via tonal correction. The developed tonal correction approach is adaptive to the scene by taking into consideration the brightness and contrast of the blurred image. The results obtained indicate the effectiveness of this blur reduction algorithm for handshake blurred images captured by a cell-phone camera.

***Index Terms*** **—** Handshake image blur reduction, image stabilization, adaptive tonal correction, cell-phone camera, low-exposure image capture.

## 1. INTRODUCTION

When a cell-phone camera is used to capture an image, in the presence of handshakes or jitter that often occur, the captured image appears blurred. Motion deblurring or blur reduction is thus considered to be a highly desirable feature on cell-phones. Although many motion deblurring algorithms are discussed in the literature, they cannot be deployed on a cell-phone processor due to its limited memory, space, and processing power. The algorithm introduced in this paper is specifically aimed at image blur reduction for deployment on a cell-phone processor.

The existing motion deblurring algorithms can be grouped into two main categories: pre-processing and post-processing algorithms. Most pre-processing algorithms involve hardware techniques, e.g. [1]-[5], which demand extra hardware to be integrated into a cell-phone. Such algorithms are deemed unsuitable for cell-phone deployment due to the space and cost constraints.

On the other hand, post-processing algorithms, e.g. [6]-[11], utilize an inverse process of blurring via a *point spread function* (PSF) to obtain a deblurred image. In general, blind image deconvolution techniques do not generate visually acceptable image quality unless the motion causing the blur is known and can be parameterized by a specific and often a simple motion model, such as constant velocity motion or linear harmonic motion as discussed in [12]-[14]. Since, in practice, such assumptions do not hold, and these algorithms are computationally quite demanding, they are not considered suitable for deployment on the cell-phone platform. In [15], a computationally expensive color detection technique was used to enhance images taken at low-exposure setting for blur removal.

Our solution presented in this paper takes into consideration the constraints of the cell-phone platform. We utilize only one image that is automatically captured electronically at a lower exposure setting immediately after an auto-exposure image is taken. Due to its lower exposure time, the blur is often removed or significantly reduced. However, this is achieved at the expense of getting a darker looking image. The challenge here is to enhance the appearance of the low-exposure image in a way which takes into consideration the characteristics of the blurred image. In this paper, we have adopted this approach as it is deemed to be suitable for deployment on the cell-phone platform noting that it is designed to be computationally efficient and not to involve any assumption or prior knowledge of the handshake motion.

The enhancement of a low-exposure image can be achieved simply by performing tonal correction. Tonal correction is widely used to adjust the appearance of an image on digital display devices and for photo enhancement [16]. In what follows, an adaptive tonal correction algorithm is introduced to achieve image blur reduction based on a low-exposure image.

## 2. ADAPTIVE TONAL CORRECTION

The adaptive tonal correction (ATC) algorithm presented here uses the low-exposure or darker looking image as its input and enhances its appearance via tonal correction by making use of the mean (brightness) and variance (contrast) of the original blurred image in an adaptive manner. The main contribution here thus consists of an automatic process by which the tonal correction is done.

Fig. 1 shows a typical tonal correction curve by which input intensity values corresponding to the three primary colors (R, G, B) can get mapped into the output intensity values. Basically, a tonal correction curve performs histogram shifting by moving the mean of the darker input image toward the brighter side of the histogram. In order to have a single tonal curve parameter to adjust, and also not to have any intensity saturation in the output image, the following tonal curve equation is considered in our ATC algorithm:

$$f(x) = \frac{\ell og(\alpha x - x + 1)}{\ell og \alpha} \tag{1}$$

where $x$ denotes pixel values of the input image, and $\alpha$ is a parameter altering the brightness level. The optimal value of $\alpha$ is considered to be the one that makes the brightness of the enhanced image equal to the brightness of the blurred image.

This correction also improves the image contrast. To further improve the contrast, a second tonal correction curve can be used to match the contrast of the blurred image. Among various possible curve functions (*tangent-hyperbolic, odd exponential, rise cosine, logarithmic, and arc-tangent*), we have considered the following function since it requires only one parameter to adjust while not causing any intensity saturation:

$$g(x) = \frac{\arctan(\beta(f(x) - 0.5)) + 0.5)}{2\tan(\beta/2)} \tag{2}$$

where $\beta$ is a parameter altering the contrast level. The optimum value of $\beta$ is taken to be the one that makes the contrast of the enhanced image equal to the contrast of the blurred image. To obtain the optimum parameter values in a computationally efficient manner, the *binary search* approach [17] is used.

## 3. COMPUTATIONAL COMPLEXITY

A typical deblurring algorithm involves two-dimensional deconvolution, which is not computationally efficient to perform on a cell-phone processor. For an image of size ($N$x$M$), a typical deconvolution algorithm requires *4(N+M)NM* operations. While the tonal correction curves can be simply implemented via *look-up tables*. The two tonal curves can also be combined into one composite curve. Thus, only one look-up table is in fact needed to map the input into the output intensity values. The optimal parameters are often reached within 5 iterations. Therefore, a typical run for ATC involves *2*x*5* look-up tables and 10*(MN)* operations, noting that on most cell-phone processors it takes one clock cycle per look-up table. In other words, for a 256x256 image, the ATC algorithm takes 200 times fewer operations than a typical image deconvolution algorithm.

Furthermore, the memory requirement of ATC is relatively low since memory space is only needed for the look-up tables. Every tonal correction curve for $\alpha$ or $\beta$ needs *256*x*2* bytes of memory space for an 8-bit quantized image. In this study, $\alpha$ was varied from 1~20 with 1.0 step size and $\beta$ was varied from 1~5 with 0.3 step size. This made the required number of curves about 300, or the required memory space less than 150 Kbytes.

## 4. ATC EFFECTIVENESS

Ideally, any image blur can get removed by keep lowering the exposure time or level. Obviously, in practice, it is not possible to lower the exposure time indefinitely because ATC introduces an unacceptable level of color distortion if the exposure level is set too low. In addition, the image noise may become more noticeable. These issues are discussed in the following subsections.

### 4.1. **Color distortion**

Color distortion is usually measured by the CIELAB color difference $\Delta E$ given by (3), which is the Euclidean distance between the true color image and the distorted one in the $L^*a^*b^*$ color space [18],

$$\Delta E = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\Delta C_{ij} \tag{3}$$

$$\Delta C_{ij} = \sqrt{\Delta L^{*2}_{ij} + \Delta a^{*2}_{ij} + \Delta b^{*2}_{ij}}$$

where $\Delta L^*$, $\Delta a^*$, and $\Delta b^*$ are the three color component differences in the $L^*a^*b^*$ color space. As discussed in [19], $\Delta E$ can be classified into three different levels to reflect the degree of color distortion as perceived by humans. As listed in Table 1, the color difference is hardly perceptible when $\Delta E$ is smaller than 3; is perceptible but remains acceptable when $\Delta E$ is between 3 and 6; and is usually not acceptable when $\Delta E$ is larger than 6.

Table 1. Color distortion visual quality [19].

| | |
|---|---|
| $\Delta E$<3 | *Hardly perceptible* |
| 3<$\Delta E$<6 | *Perceptible but acceptable* |
| $\Delta E$>6 | *Not acceptable* |

### 4.2. Image noise

Typical SNRs in images captured by a digital camera is shown to vary from 10dB to 40dB depending on the ISO setting [20]. Here, both the blurred and low-exposure images are assumed to have been captured with the same ISO setting.

As discussed in [21], applying ATC to the low-exposure image alters the noise power as follows:

$$\sigma^2_{out} = \int [f(x) * g(x)]^2 p(x)dx \tag{4}$$

where $p(x)$ denotes the PDF of the image plus noise. Since neither *f(x)* nor *g(x)* is a linear function, equation (4) does not have an analytic solution. In most cases, the application of *g(x)* is not required. Therefore, by considering only *f(x),* for small ranges of *x, f(x)* can be estimated by a linear function. Equation (5) gives the slope of *f(x)* in a small range of $x$ close to $x1$,

$$m = \left.\frac{df(x)}{dx}\right|_{x=x1} = \frac{\ell og\alpha}{x1 + \frac{1}{\alpha - 1}} \quad (5)$$

for $f(x)=mx+b$. Consequently, the noise power in the output image can be written as

$$\sigma_{out}^2 = m^2 \sigma_{in}^2 \quad (6)$$

Since the same relationship holds for the image power, for all practical purposes, the SNR in the ATC enhanced image stays the same as the blurred image. Therefore, as compared to image noise, color distortion plays a more prominent role in the effectiveness of ATC.

## 5. EXPERIMENTAL RESULTS

A study was done based on 240 images corresponding to 12 different scenes to obtain the effectiveness of ATC for blur reduction or image stabilization. Fig. 2 shows the average amount of color distortion caused by ATC for different amounts of exposure time. As shown in this figure, an exposure level reduction of 20% generated no perceivable visual color distortion. An exposure setting of 30% generated color distortion in the acceptable range. Fig. 2 also shows the average $\alpha$ and brightness increase by ATC for different exposure levels. The ATC processing with $\alpha$ >10 produced color distortion higher than the acceptable level. Fig. 3 illustrates three sample captured images (blurred and low-exposure at an exposure setting of one-third the nominal). This figure also shows the outcome of our blur removal ATC algorithm.

## 6. CONCLUSION

In this paper, an adaptive tonal correction algorithm is introduced to reduce handjitter blur in images captured by a cell-phone camera based on a low-exposure image that is captured electronicly immediately after an image is taken. The main attributes of this algorithm are its low computational complexity, adaptiveness to the brightness and contrast of the scene captured, making no assumption about the motion blur, and not requiring any manual intervention. It has been shown that the effectiveness of this algorithm is limited by the introduced color distortion as a result of the low-exposure setting. In our experimentation, one-third reduction in the exposure setting lead to visually acceptable levels of color distortion.

## 7. ACKNOWLEDGMENT

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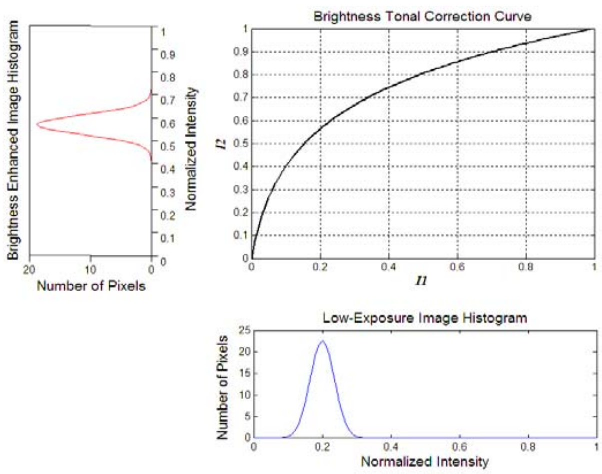


**Fig. 1. Tonal correction curve for brightness enhancement.**

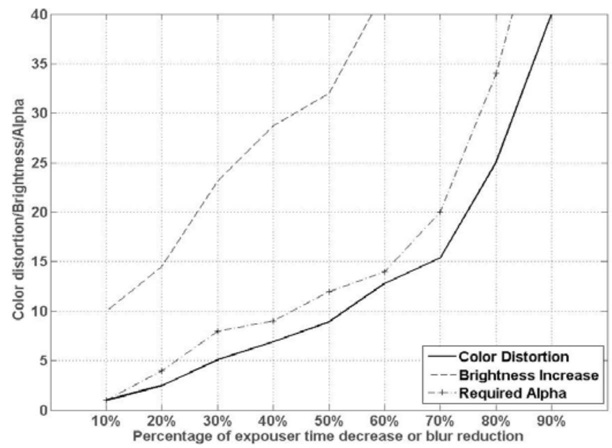


**Fig. 2. Amount of color distortion versus percentage of exposure time decrease or blur reduction.**

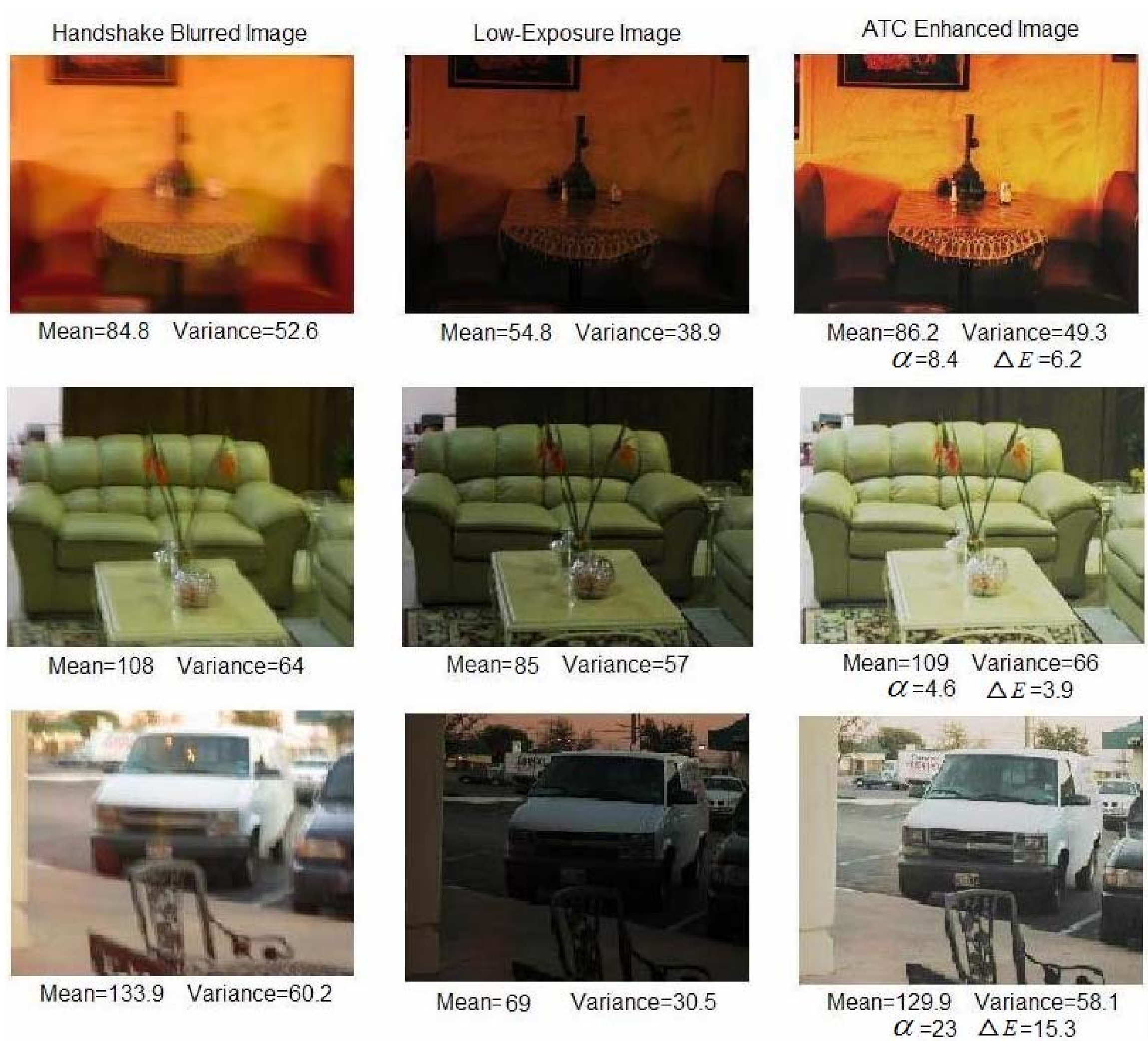


**Fig. 3. Left column: handshake blurred images - center column: low-exposure images - right column: ATC enhanced images.**