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IMAGE 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. 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.

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

I. 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. Motioned de- blurring or blur reduction is thus considered to be a highly desirable feature on cell- phone. Although many motion de-blurring algorithms are discussed in the literature, they cannot be employed on a cell-phone processor due to its limited memory, space, and processing power. The algorithm introduced in this project is specifically aimed at image blur reduction for deployment on a cell-phone processor.

The existing motion de-blurring algorithms can be grouped into two main categories: pre-processing and post-processing algorithms. Most pre-processing algorithms involve hardware techniques, which demand extra hardware to be integrated into a cell- phone. On the other hand, post processing algorithms utilize an inverse process of blurring via a point spread function (PSF) to obtain a de-blurred image.

In general, blind image de-convolution 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. 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. Here an adaptive tonal correction algorithm is introduced to achieve image blur reduction based on a low-exposure image.

II. IMPLEMENTATION

Tonal corrections are those adjustments and changes you make to the brightness and contrast of your image. For years, Photoshop's workhorse tonal correction has been the Levels control and the Curves dialog box, both of which can be applied either destructively or as adjustment layers. The overall approach consisted of taking an image, converting it into its spatial frequencies, developing a point spread function (PSF) to filter the image with, and then converting the filtered result back into the spatial domain to see if blur was removed. This was performed in several steps, each of which built from having a greater understanding of the one preceding it.

The first step was taking a normal (i.e. Not blurred) image, creating a known blurring PSF, and then filtering the image so as to add blur to it. The next step was removing this blur by various methods, but with the information about the PSF that was used to create the blur. After that, de-blurring was performed without knowing anything about nature of the blurring PSF, except for its size. Finally, an algorithm was developed for removing blur from an already blurry image with no information regarding the blurring PSF.

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.3 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 our ATC algorithm:

$$f(x) = \log(\alpha x - x + 1) / \log\alpha$$

Where x denotes pixel values of the input $f$imfFage, and D is a parameter altering the brightness level. The optimal value of D 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:

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

Where β is a parameter altering the contrast level. The optimum value of E 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 is used.

Image blur occurs often when using a cell- phone camera due to handshakes or jitter. Although there exits many motion de-blurring 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 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.

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.

Reproducing natural and artificial scenes on display devices of a limited dynamic range (contrast) is a challenging problem in photography, cinematography, printing and visualization. So far, the best results are achieved when each image is manually adjusted on the target display. This, however, is a tedious task that often requires expert skills. The question arises whether the manual adjustments can be replaced with a computational algorithm.

We address this question by demonstrating that the image reproduction tasks can be formulated as an optimization problem, in which the best tradeoff between preserving contrast in all ranges of a tone-scale is found. Such optimization is driven by a perceptual metric that weights contrast distortions according to their visibility and importance. Tone- mapping should not only ensure that the resulting pixel values are in the range 0-255, but also that the actual tones shown on a particular display of certain capabilities will convey desired image content.

This is especially important with the recent developments in the display technologies (LCD, LCoS, PDP, DLP, OLED, e-paper, backlight modulation and the variety of applications in which they are employed (home entertainment, mobile displays, electronic books, cockpit displays, etc.). All these display devices can differ dramatically in their peak brightness, contrast (dynamic range) and black level, and can change their characteristic with the viewing conditions (sunlight vs. Office light).

Therefore, it cannot be expected that the same image shown on different devices will produce the desirable appearance. Tone-mapping with no knowledge of the target display is not a fully defined problem, similarly as gamut mapping with no knowledge of the target gamut. We propose a tone-mapping operator that produces the least distorted image, in terms of visible contrast distortions, given the characteristic of a particular display device.

The distortions are weighted using the human visual system (HVS) model, which accounts for all major effects, including luminance masking, spatial contrast sensitivity and contrast masking. Such tone mapping operator is naturally formulated as an optimization problem, where the error function is weighted by the HVS model and constraints are dictated by the display limitations. We demonstrate that the problem can be solved very efficiently if the error function is based on higher order image statistics and the non-linear optimization problem is reduced to the medium-size quadratic programming task.

A straightforward extension of our method ensures temporal coherence and makes it suitable for video sequences. The performance of our technique is validated in several less studied scenarios of tone reproduction when the viewing conditions and display capabilities vary. Our experimental study shows that images that are adaptively tone- mapped to illumination. Conditions are preferred in terms of contrast reproduction. Finally, the method is compared with other tone mapping operators.

The original goal of the tone mapping problem, as formulated by Tumbling and Rushmeier [1991], is to reproduce a scene on a display, so that the brightness sensation of a displayed image is equal or closely matches the real-world brightness sensation. The perfect match between the original and its rendering on a display or in a hard-copy format is almost never possible, as an output medium is hardly ever bright enough, offers sufficient dynamic range (contrast) and color gamut. Therefore, the rendering on an output device is a tradeoff between preserving certain image features at the cost of the others. For example, high contrast and brightness of an image can often be preserved only at the cost of clipping (saturating) certain amount of pixels in bright or in dark regions.

The choice of which features are more important should be driven by a particular application, for which an Appropriate metric could be designed, possibly involving some aspects of the visual perception. These considerations lead us to a general tone mapping framework, illustrated in Figure3.1, which is formulated as an optimization problem. Having an original image as input, which can be in HDR or any scene-referred high quality format, we want to generate a display adapted image that would be the best possible rendering of an original scene.

We assume that this goal is achieved if the response of the HVS for an image shown on the display, Drips, is as close as possible to the response evoked by the original scene, roaring. Both responses can almost never be the same as a display can only show limited dynamic range and color gamut. Also the viewing conditions, such as ambient light or luminance adaptation, differ between the original scene and its rendering, making the match even more Difficult. The solution of the optimization problem is a set of tone mapping parameters that minimizes the difference between Rorig and Rdisp.

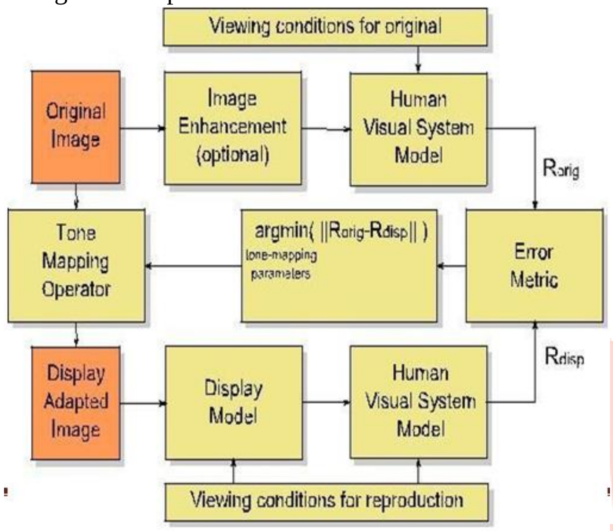
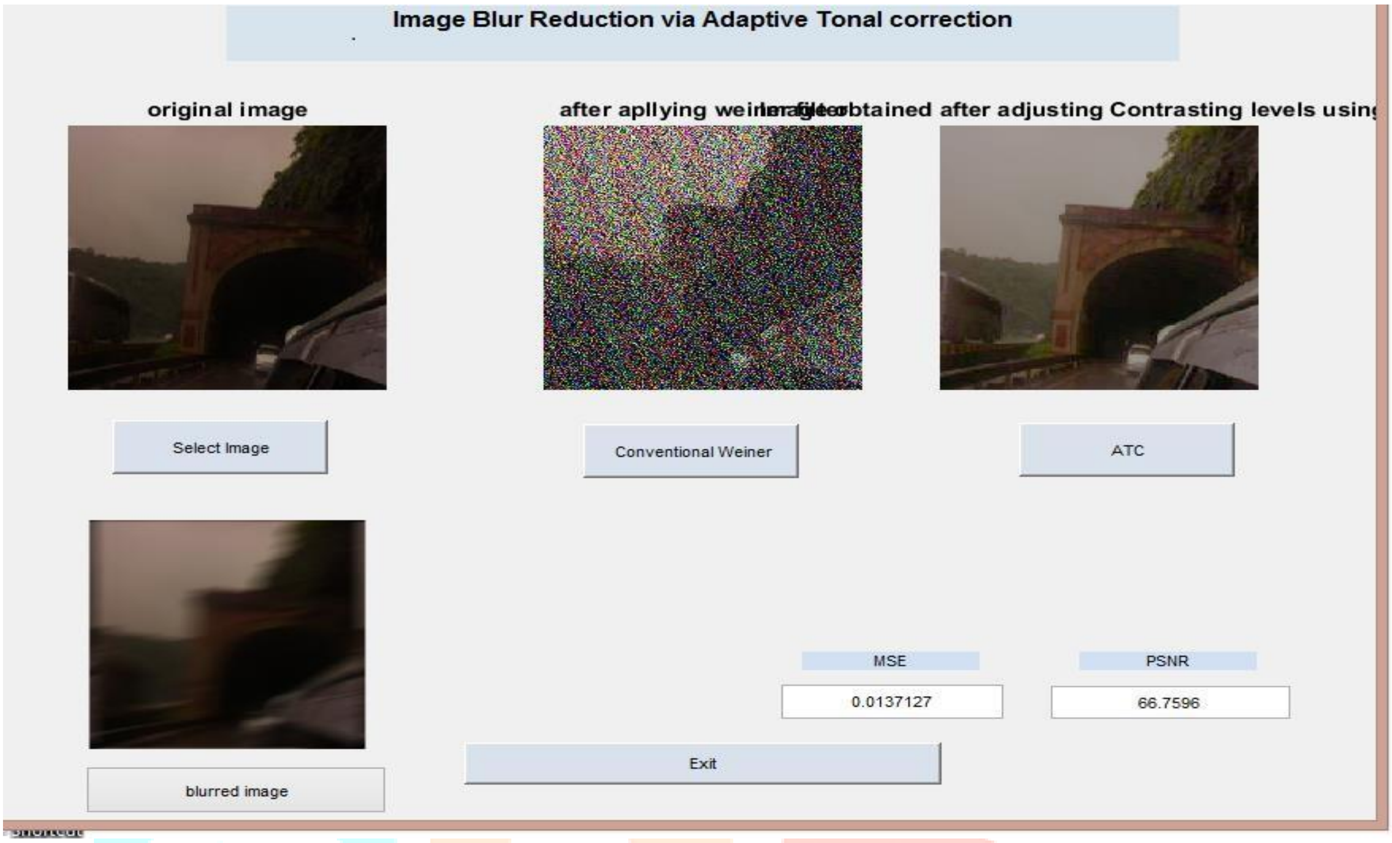


Fig: The proposed formulation of the tone-mapping problem.

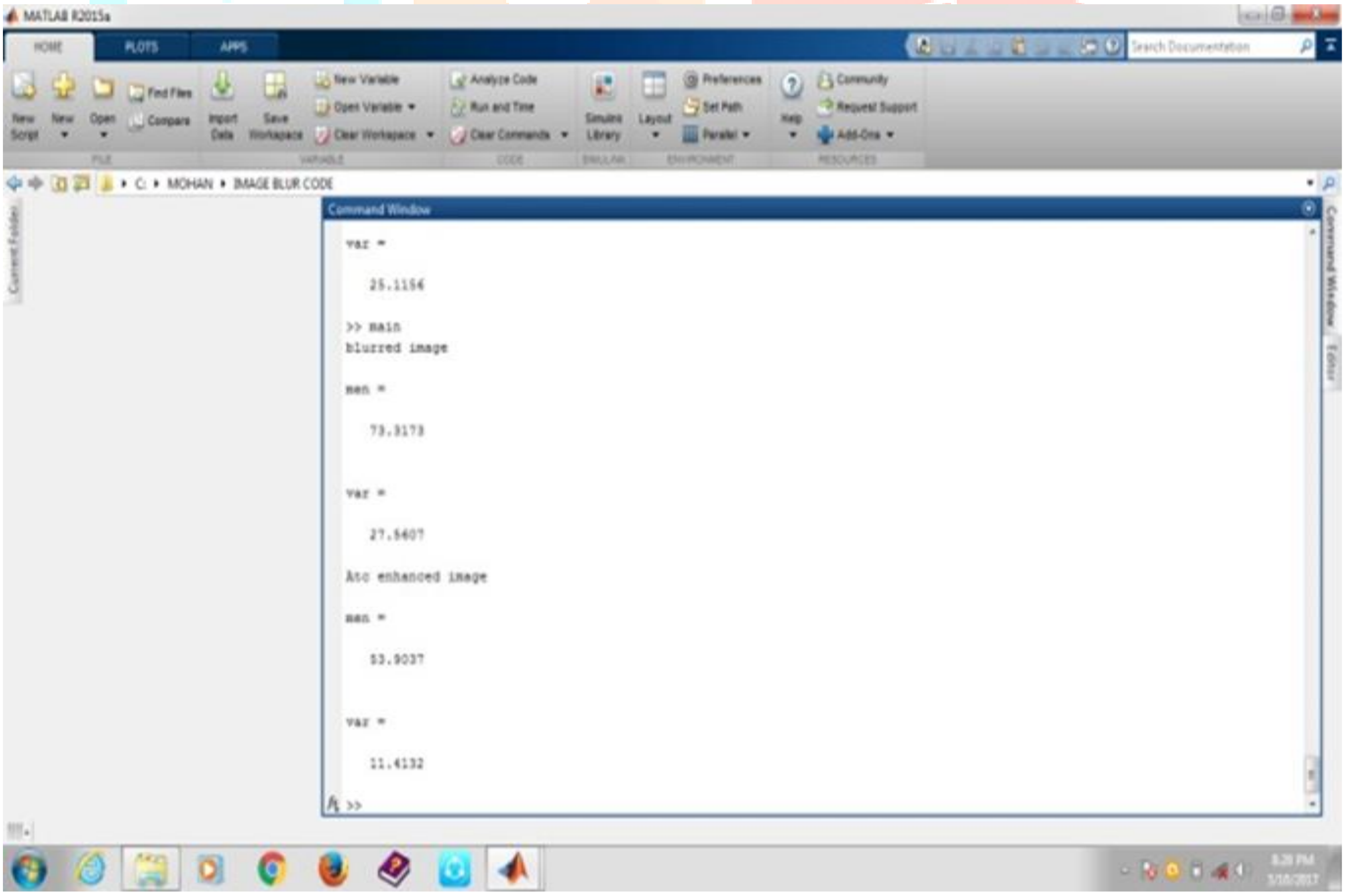
The above figure contains also a processing block for image enhancement, as many applications require reproducing images that are sharper and more colorful than the originals. The display model introduces physical constraints on devices' color and luminance reproduction. The difference is that these approaches assume Rdisp = Rorig and then invert the HVS and display models to compute a tone mapped image. If we follow this approach and compute the desired display luminance that would evoke the same sensation as a real world scene (Rdisp =Rorig), we can end up with an image that is too bright or has too much contrast for a given display. In such situation, if we apply the limitations of a display and clamp luminance values, we get Rdisp significantly different from Rorig, which is unlikely, the global minimum of our optimization problem. Furthermore, our framework can be used with arbitrary HVS and display models, while previous approaches required the models to be invertible.

The problem formulation above has been used before in the context of digital half toning for printing, but it has not been employed to derive a tone mapping operator. The major difficulty lies in the fact that even simplified models of a display, the HVS and a tone mapping operator lead to a complex non-linear optimization problem, which may exhibit local minima, or be too complex to solve in reasonable time. In the following subsections we will present a combination of such models, which are sufficiently complete to realize the goals outlined above, and at the same time lead to a standard optimization problem, which can be solved efficiently.

III. RESULTS



Results of image blur reduction for cell phone cameras via adaptive tonal correction



IV. CONCLUSION

In this paper, an adaptive tonal correction algorithm is introduced to reduce hand jitter blur in images captured by a cell-phone camera based on a low-exposure image that is captured electronically immediately after an image is taken. The main attributes of this algorithm are its low computational complexity, addictiveness 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.

REFERENCES

[1]. Canon Inc. "http://www.canon.com.my/techno/optical/optical_b.htm," 2004.
[2]. Nikon Inc. "http://www.nikon.co.jp/main/eng/society/techrep/tr8-vr_e.htm," 2004.
[3]. Canon Inc., "http://www.canon.com/technology/optics/shakecorrect_ shift/index.html," 2003.
[4]. Canon Inc., "http://www.canon.com/technology/optics/vap/content. html," 2003.
[5]. Canon Inc., "http://www.roper.co.jp/html/tefbin.htm," 2003.
[6]. Y. Jianchao, "Motion Blur Identification Based on Phase Change Experienced After Trial Restorations," Proceedings of IEEE ICIP Conference, vol. 1, pp. 180-184, 1999.
[7]. A. Stern, I. Kruchakov, E. Yoavi, and N.S. Kopeika, "Recognition of Motion-Blurred Images by Use of the Method of Moments," Applied Optics, vol. 41, pp. 2164-
[8]. 2171, 2002.
[9]. Y. Zhang, C. Wen, and Y. Zhang, "Estimation of Motion Parameters from Blurred Images," Pattern Recognition Letters, vol. 21, pp. 425-433, 2000.
[10]. Y. Yitzhaky, G. Boshusha, Y. Levy, and N. Kopeika, "Restoration of an Image Degraded by Vibrations Using Only a Single Frame," Optical Engineering, vol. 39, pp.2083-2091, 2000.
[11]. Y. Yitzhaky, I. Mor, A. Lantzman, and N. Kopeika, "Direct Method for Restoration of Motion-Blurred Images," Journal of Optical Society of America, vol. 15, pp. 1512-1509, 1998.
[12]. M. Banham, A. Katsaggelos, "Digital Image Restoration, IEEE Signal Processing Magazine, pp. 24-41, Mar. 1997.
[13]. D. Tull, A. Katsaggelos, "Regularized Blur-assisted Displacement Field Estimation", Proceedings of IEEE ICIP Conference, vol.3, pp. 85-88, 1996.
[14]. D. Tull, A. Katsaggelos, "Iterative Restoration of Fastmoving Objects in Dynamic Image Sequences," Optical Engineering, vol. 35, pp. 3460–3469, December 1996.
[15]. A. Patti, M. Sezan, M. Tekalp, "Super-resolution Video Reconstruction with Arbitrary Sampling Lattices and Nonzero Aperture Time," IEEE Transactions on Image Processing, vol. 6, pp. 1064–1078, August 1997.
[16]. T. Pajdla and J. Matas, "Bayesian Correction of Image Intensity with Spatial Consideration", ECCV, LNCS 3023, pp. 342–354, 2004.
[17]. G. Rafael C., R. Woods, Digital Image Processing, 2nd edition, Prentice-Hall, NJ, 2002.
[18]. T. Biedl, T. Chan, E. Demaine, R. Fleischer, M. Golin, J. King, J. IanMun, "Fun-Sort— or the Chaos of Unordered Binary Search", Discrete Applied Mathematics, vol. 144, pp. 231-236, January 2004.
[19]. CIE Recommendation on Uniform Color Spaces, Color Difference Equations, Psychometric Color Terms, Supplement No. 2 to CIE Publication No.15 (E.-1.3.1) 1971/(TC-1.3.), 1978.
[20]. J. Hardeberg, Acquisition and Reproduction of Colour Images: Colorimetric and Multispectral Approaches, PhD Dissertation - Docteur de l'Ecole Nationale Supérieure des Télécommunications, Paris, France, Feb. 1999.
[21]. ISO Recommendation on Determination of ISO Speed, No. 12232,1998.
[22]. G. Holst, CCD Arrays Cameras and Displays, 2nd edition,