Fast and Better Measure of Image Sharpness

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I. Introduction

SHARPNESS measure has been used in many engineering and scientific applications including, for example, auto-focusing and astigmatism correction in the scanning electron microscope or transmission electron microscope [2], [6]. Note that the photographs taken by microscopes are quite well structured than those taken by digital cameras. The former photos may contain much more texture regions than latter ones. Thus, the sharpness metrics for the former ones mainly focus on the sharp edges separating texture regions. However, needless to say, the sharpness metrics can be applied to any photos. The main objective of this paper is detecting blurry photos from sharp ones taken by digital cameras. Digital photographs are far more complex and unstructured.

Even with reasonable performance of auto-focusing algorithms image degradation is unavoidable unless entire robustness is guaranteed in the system [10]. In order to automatically select blurry pictures among a pool of digital pictures, various measures of sharpness or blurriness have recently been proposed [5], [10], [11], [13], [14], [15], [16], [18]. The simplest measure is the ratio of high frequency components to low frequency components. Blurry pictures tend to become smoother than crisp images, and contain less number of edges.

Blurry pictures may have smaller gradients in the edge regions and less energy in high frequency components. Thus, given input images are usually transformed by DCT or DWT, and are quantized to see how much high frequency components exist. Some simple approaches count occurrence of non-zero DCT coefficients [12]. Larger number of non-zero coefficients means that the image is sharper. Sum of high-frequency components larger than threshold value [9] also plays the similar role.

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Blurry pictures may have smaller number of grey-level values than sharp ones. Thus, counting number of bins in the histogram of the grey-level values can be a good solution [9]. It is assumed that a sharper image has a larger number of bins. Extreme case is uniformly distributed histogram with maximum number of bins. In the same context, entropy can be used to measure sharpness. If the probability of occurrence of each grey-level is low, the entropy is high and vice versa. In other words, sharp image has high entropy. The probability distribution can be a good indicator of sharpness. Sharper image has larger variance [6] or larger kurtosis [19] values.

Blurry images are highly correlated while sharp images are not. Thus, auto-correlation [2] can be a good metric for sharpness. Derivatives [4] can be another good indicator. For example, the first-order derivative (i.e., gradient) which acts as a high-pass filter can be a good indicator. Sharp images have large derivative values.

On the other hand, wavelet-based blurriness or sharpness estimation methods have been proposed in [11], [14], [17]. For example, Rooms et al. [15] have proposed the Lipschitz exponent-based method which suits well only for medical applications such as microscope images of cell nuclei. Ferzli and Karam [7] propose a sharpness measure based on the Lipschitz regularity for differentiating between edges and noise singularities. This metric performs quite well when dealing with a moderately noisy environment. On the other hand, special characteristics of human visual system can be exploited to provide reasonable sharpness metric [8].

Batten et al. [3] evaluate the gradient measure, auto-correlation measure, frequency-domain measure, and variance measure, and conclude that the last measure is better than others in terms of computing time and immunity to noise. The gradient measure is most susceptible to noise, while the variance measure is largely insensitive. The auto-correlation measure is usually strictly unimodal, but has poor reproducibility. Reproducible measure has a sharp peak. A strictly unimodal sharpness measure has a single peak at the best focus and monotonically decreasing away from this peak. The implementation cost of the frequency-domain measure is significant. Another air comparison of various methods is available in [7].

Most of the aforementioned methods aim at auto-focussing and astigmatism correction. On the other hand, to make better classification of pictures in the sense of sharpness many measures have additionally been proposed. A good measure should be invariant to pictures and picture contents, and well correlate with perceived sharpness. Shaked and Tastl [16] have developed an algorithm to estimate the overall sharpness of a picture to determine how much sharpening should be applied to each picture. They estimate the global sharpness of a picture by a single scalar value. However, the single value criterion could not provide sufficiently invariant measure with various pictures. In order to solve this problem Banerjee et al. [1] have segmented pictures based on the rule-of-thirds to exploit local features. Lim et al. [10] have developed an effective, efficient algorithm which uses several global figure-of-merits computed from local image statistics.

In this paper, we propose a new measure based on computing the prediction residue between neighboring pixels in images and computing variance to measure the sharpness or blurriness without reference. This measure is totally different from the previous variance measure [6]. Previous measure computes variance of the pixel values themselves, while the proposed measure computes variance of the prediction residue of neighbor pixels. This paper shows why the proposed measure is mathematically reliable, easy to implement, and fast. In addition, the feasibility of the proposed measure is shown with thorough experiments with various images. Regardless of the detection accuracy, existing measures are computation-intensive. However, the proposed measure in this paper is not demanding in computation time. For this measure, transform is not necessary. Complex and time-consuming operations are not requested. Computing prediction residue for P sample pairs and computing variance are sufficient, where P is approximately 300 among $M \times N$ sample population. The prediction operator is just computing difference between adjacent pixels. In addition, accuracy of the proposed measure is very high.

II. Theoretical Background

A. Previous Variance Measure

The variance of an image is a good measure of sharpness [6]. However, its performance needs to be further improved. The variance for sharpness measure is defined as follows:

$$\sigma_v^2 = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[g(x,y) - \bar{g}]^2, \qquad (1)$$

where $\bar{g}$ represents the mean intensity of $g(x,y)$.

Note that the distribution, i.e., histogram of a real image is, in general, neither Gaussian nor Laplacian. On the other hand, real images are highly correlated. The variance measure in Eq. (1) does not take this correlation into account.

B. New Variance Measure

In general, images are highly correlated. When there is significant correlation between successive samples, it should be possible to predict the value of any given sample, with a reasonably high degree of accuracy, from some of the preceding samples. The difference between the actual image and the predicted version is often called prediction residue or prediction error. If the prediction algorithm is reasonably good, most of the values in the residue will be zero or very close to it. This in turn means that the distribution function of the predicted signal will be peaky. It is the decorrelation process in image compression. When the image is decorrelated, its distribution is nearly Gaussian or Laplacian-like.

There are many decorrelators available in the literature. The simplest predictor for an image is one that uses the previous pixel in the image as the prediction of the current pixel. Formally, if we denote the current pixel by $g(x,y)$ and the previous pixel by $g(x,y-1)$, the prediction $\hat{g}(x,y)$ of $g(x,y)$ is given by $\hat{g}(x,y) = g(x,y-1)$. In this case, the prediction error, $e(x,y)$ is nothing but the difference between the adjacent pixels. Hence, $e(x,y) = g(x,y) - g(x,y-1)$.

Let ρ be the coefficient of correlation between $g(x,y-1)$ and $g(x,y)$. Suppose that relationship between $g(x,y-1)$ and $g(x,y)$ can be expressed as $g(x,y) = \rho g(x,y-1) + \varepsilon(x,y)$, where $\varepsilon(x,y)$ denotes a white noise and is uncorrelated with $g(x,y-1)$. Then, the variance of $e(x,y)$ is given as $V\{e(x,y)\}=V\{(\rho-1)g(x,y-1)+\varepsilon(x,y)\}$ or $V\{e(x,y)\} = (\rho-1)^2 V\{g(x,y-1)\}+V\{\varepsilon(x,y)\}$.

Generally, $V\{\varepsilon(x,y)\}$ is much smaller than $V\{g(x,y-1)\}$ except edge points in images. From some experiments, we found that ρ of the blurred images tends to be larger than that of the original images. The number of edge points of the original

Baboon image is relative larger than that of the blurred image. These imply that the blurred images has much smaller variance of $e(x,y)$ than the original.

The variance for sharpness measure of using residue prediction is defined as follows:

$$\sigma_p^2 = \frac{1}{M(N-1)} \sum_{x=1}^{M} \sum_{y=1}^{N-1} [e(x,y) - \bar{e}]^2, \quad (2)$$

where $\bar{e}$ represents the mean intensity of $e(x,y)$'s. Eq. (2) can be rewritten with different predictor or different organization scheme of the prediction residue. Let u be the prediction residue vector. Then, the prediction residue vector can be modeled as Laplacian-like distribution as follows:

$$f_u(u) = \frac{1}{2\sigma_p} e^{-|u|/\sigma_p}. \quad (3)$$

Note that variance is still a good measure of the Laplacian-like distribution in Eq. (3) showing dispersion of the sample values although the best dispersion measure is

$$\sigma_l^2 = \frac{1}{M(N-1)} \sum_{x=1}^{M} \sum_{y=1}^{N-1} \left| e(x,y) - \tilde{e} \right|.$$

where $\tilde{e}$ stands for the median of $e(x,y)$'s. If the variance of the Laplacian-like distribution is large, it shows that adjacent samples are less correlated. As a consequence, it can imply that the image contains many high frequency components. The prediction residue between adjacent samples in the blurry images is smaller than that in the sharp images. From a set of test images variance values are listed in Table I. The figures are different from filter to filter, resolution by resolution, camera by camera, and so on. The figures in Table I are obtained by using Gaussian low-pass filter with MATLAB fspecial function. In order to reduce the computation time considerably, we take 30 sample pairs and compute measure based on the prediction residue of the sample pairs since the Baboon image size is small (i.e., 256×256). The number of sample pairs can be adjusted to meet the requirements such as computing time and accuracy of the detection.

As shown in Table I, the variance of the sharp Baboon is 2,135 while that of the blurred image is just 3 computed with 30 sample pairs. The variances of the blurred images depend on the degree of the blurriness. More blurred images may have smaller variances, and less blurred ones larger variances. The variance figures in Table I are obtained from the sharp images. The variances of blurry images are obtained from blurry images artificially blurred version of the corresponding sharp images. Note that these figures justify our assumption.

TABLE I

VARIANCES OF A SET OF STANDARD TEST IMAGES: SHARP ONES AND THEIR BLURRED COUNTERPARTS

Images	σ_p^2 of sharp image	σ_p^2 of blurred image
Airplane	33.9	1.4
Baboon	2135.6	3.3
Lenna	11.8	1.9
Peppers	56.9	6.4
Peppers2	27.1	3.8
Sailboat	220.0	3.8
Tiffany	14.0	0.4

III. EXPERIMENTS

For the first experiment we take 140 photographs using a digital camera of spatial resolution 960×1280. Among them 70 images are realistically blurry, and the rest of them are sharp or partially blurry. For the second test, 200 sharp color photographs of spatial resolution 1536×2048 are taken. Then, the resolution is adjusted to 960×1280. We add artificial blur to these images using Gaussian and motion filters. The fspecial function is used for the blurring.

In these experiments that use both sets of test images we compute variances (see Figure 1) with 300 sample pairs from $M \times N$ sample population. The horizontal axis shows the image number while the vertical axis shows the variance value of each image. As is expected, the sharp images have larger variances than blurry ones. For each image number in Figure 1, the red one stands for the variance of the associated sharp image. The blue one and green one represent the variances of motion-blurred and Gaussian-blurred images, respectively. However, unfortunately, the variance of the blurry one can infrequently be larger than sharp one as shown in Figure 1. Similarly, the variance value of the blurry one can be relatively large. Thus, it is not easy to decide appropriate threshold value that can perfectly separate sharp images from blurry ones. Such threshold values may not exist due to imperfect measures. In other words, false alarm is inevitable. Motion-blurring is easier than Gaussian-blurring in this experiment since that variance is far smaller than this variance. If the degree of motion-blurring is insignificant, the false alarm rate will

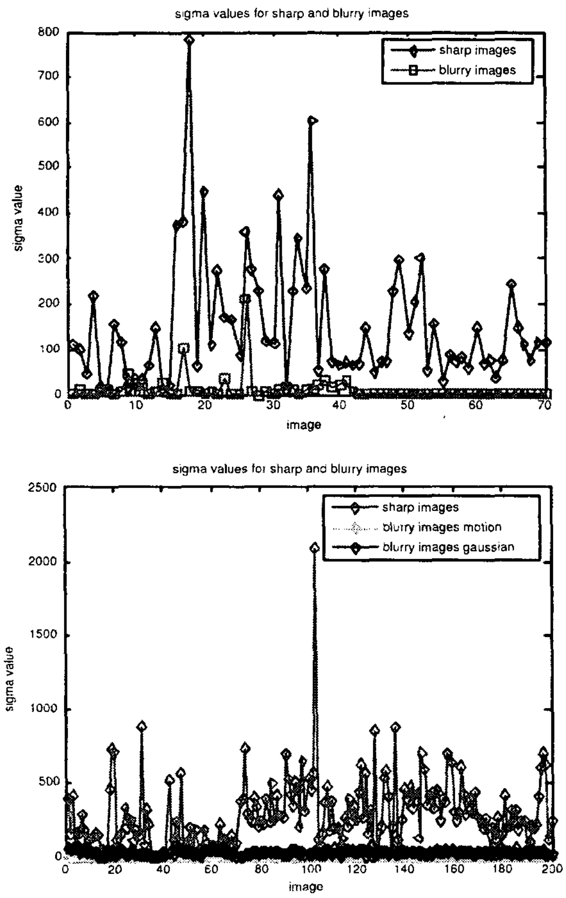

Fig. 1. Variances of 140 images (top) with 70 sharp ones (blue) and 70 blurry ones (red), those of 600 images (bottom) with 200 sharp (red), 200 motion-blurred (blue), and 200 low-pass filtered ones (green) computed using the proposed measure in this paper

increase accordingly. However, the degree of motion-blurring by novice photographers is, in general, more serious than that of this experiment.

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