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Efficient Sharp Digital Image Detection Scheme

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Abstract

In this paper we present a simple, efficient method for detection of sharp digital images. Recently many digital cameras are equipped with various autofocusing functions to help users take well-focused pictures as easily as possible. However, acquired digital pictures can be further degraded by motion, limited contrast, and inappropriate amount of exposure, to name a few. In order to decide whether to process the image or not, or whether to delete it or not, reliable measure of image quality to detect sharp images from blurry ones is needed. This paper presents a blurriness/sharpness measure, and demonstrates its feasibility using extensive experiments. This method is fast and easy to implement, and accurate. Regardless of the detection accuracy, existing measures are computation-intensive. However, the proposed measure in this paper is not demanding in computation time. Needless to say, this measure can be used for various imaging applications including autofocusing and astigmatism correction.

Keyword: detection of sharp digital images, autofocusing functions, astigmatism correction, blurriness/sharpness measure, computation-intensive, digital camera

I. Introduction

Sharpness measure has been used in many engineering and scientific applications including, for example, auto-focusing and astigmatism correction in the scanning microscope or transmission electron microscope [1, 2]. 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 high-quality (really sharp) photos from low-quality ones (blurred, noised, out-of-focus, etc.) taken by digital cameras. Digital photographs are far more complex and unstructured.

Nowadays, high-quality and low-cost image systems, such as digital cameras, gain increasing attention as digital technology advances. Although a user can take hundreds of pictures per day, it is not easy to look through all the pictures to evaluate the acquisition quality of each image. If we have a simple measure of quality, degraded images can be automatically deleted or they can go through an enhancement process for better quality. Typical causes of blurry pictures include: out-of-focus, camera jitter, moving objects, limited contrast and an inappropriate amount of exposure. Of course, intentionally blurred photos can be taken for special effects.

In this paper, to detect sharp images from low-quality ones, we propose a new evaluation method based on computing the prediction residue between neighboring pixels in

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images and computing variance to measure the quality of photographs without reference. This paper shows why the proposed method is mathematically reliable, easy to implement, and fast. In addition, the feasibility of the proposed method 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. The prediction operator is just computing difference between adjacent pixels. In addition, accuracy of the proposed method is very high.

II. Overview of the previous approaches

Even with reasonable performance of autofocusing algorithms image degradation is unavoidable unless entire robustness is guaranteed in the system[3]. In order to automatically select blurry pictures among a pool of digital pictures, various measures of sharpness or blurriness have recently been proposed[3-9]. 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 as illustrated in Figure 1.

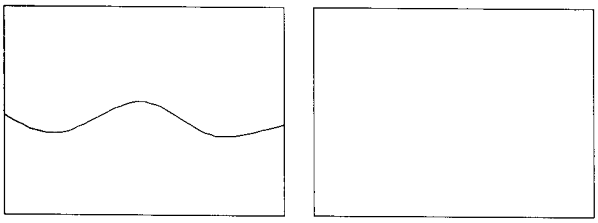

Fig. 1. Illustration of blurry (left) and sharp (right) edges

As shown in Figure 1, 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[10,11].

As shown in Figure 1, 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[11]. 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 andvice versa. The probability distribution can be a good indicator of sharpness. Sharper image has larger variance[2] or larger kurtosis[12] values.

As shown in Figure 1, blurry images are highly correlated while sharp images are not. Thus, auto-correlation[1] can be a good metric for sharpness. Derivatives[13] can be another good indicator.

On the other hand, wavelet-based blurriness/sharpness estimation methods have been proposed in [5], [7], [14]. 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[16] 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[17].

Batten et al. [18] 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.

Most of the aforementioned methods aim at auto-focusing and astigmatism correction. A good measure should be invariant to pictures and picture contents, and well correlate with perceived sharpness. Shaked and Tastl [8] 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. [19] have segmented pictures based on the rule-of-thirds to exploit local features. Lim et al. [3] have developed an effective, efficient algorithm which uses several global figure-of-merits computed from local image statistics.

III. Theoretical background

1. Previous Variance Measure

The variance of an image is a good measure of sharpness [2]. However, its performance needs to be further improved. The variance for sharpness measure is defined as follows:

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

where g(x,y) is the intensity of the pixel value, and $\bar{g}$ represents the mean intensity of all g(x,y)'s.

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.

Figure 2 shows an original, sharp Baboon image (left) and its blurred version (right). Their histograms are shown in Figure 3. It is obvious that the sharp image histogram (solid line) is flatter than theblurred one (dash-dot line). The standard deviations of the original and blurred images are 1,808 and 1,022 respectively. Note that large difference between those two figures is desirable. However, in this case, the ratio is around 1.8.

Fig. 2. Original Baboon image (left) and blurred Baboon image (right)

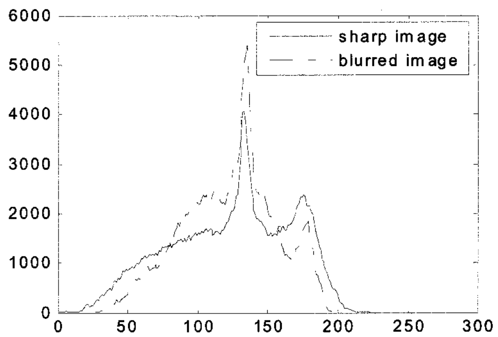

Fig. 3. Distribution of gray-level values of original Baboon image (solid line) and blurred image (dash-dot line)

2. 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.

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

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

where $\bar{e}$ represents the mean intensity of prediction errors 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:

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

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 as shown in Figure 1. The prediction residue between adjacent samples in the blurry images is smaller than that in the sharp images. In other words, velocity of changing neighboring pixels' values in sharp images is higher than that in blurry ones

$$\frac{\partial g(x,y)_{sharp}}{\partial x} > \frac{\partial g(x,y)_{blur}}{\partial x}$$

and thus the distributions of these values also differ (see Figure 4).

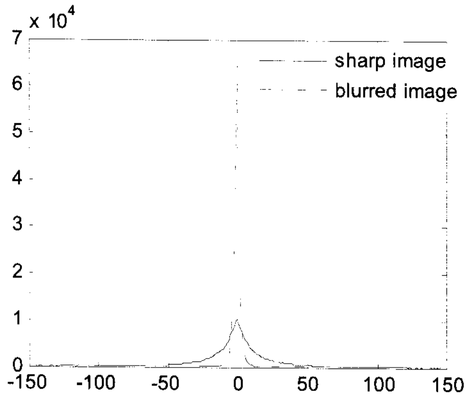

Fig. 4. Distribution of prediction residue of original Baboon image (solid line) and blurred image (dashed line)

From a set of test images variance values are listed in Table 1. The figures in Table 1 are obtained by using Gaussian low-pass filter with Matlab **fspecial** function (using the same amount of blur).

Table 1. 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	105.96	5.8
Baboon	206.6	3.1
Lenna	61.9	4.4
Peppers	56.9	6.4
Sailboat	65.9	7.6
Tiffany	68.9	3.8

As shown in Table 1, the variance of the sharp Baboon is 206.6 while that of the blurred image is just 3.1 computed with 300 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 1 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.

IV. Algorithm

The core of the algorithm is the image quality measure and the threshold value for making a decision. The measure is the variance of the prediction residue of P sample pairs among $M \cdot (N-1)$ sample population. Through the extensive experiments we found that 300 sample pairs would be enough for computing eligible variance values. And also, since $P \ll M \cdot (N-1)$, computation time of the proposed measure is notably insignificant. Deciding the threshold values for evaluation the global and local variance values is another keyof success of the algorithm. As the fixed values may cause high false alarm rate for certain type of images, we propose to use flexible threshold t1 in the middle stage of the proposed algorithm. The block scheme of the proposed algorithm is illustrated in Figure 5.

As a preprocessing, we only need to convert the input images from RGB to grey-level color. The resolutions of the digital camera we adjusted for taking photos for our experiments are 960x1280, 1200x1600 or 1536x2048.

Detection algorithm based on the new measure can be summarized as follows:

1. Compute prediction residue between adjacent pixels and reshape the image matrix Mx$(N-1)$ to 1x$(M \cdot (N-1))$.
2. Take P sample pairs periodically (i.e., every $(M \cdot (N-1))/P$ samples) from the grey-level population and compute global variance value.
3. Divide image into non-overlapping blocks of size 100x100 and compute local variances for each one using all the difference sample pairs. After getting variance values of all the blocks, obtain the local threshold t_1 by taking average value of all variances disregarding those ones that have very large values (if only there are not many of them).
4. Evaluate the global variance if it is larger than the global threshold T=60, and then compute the number of blocks with local variance values smaller than the threshold value t_1. If the number of such blocks (*NB*) is less than 60%, then the image is identified as globally sharp one. Otherwise, it contains some blurry parts (moving objects, or blurry background, etc.).
5. If the global variance is smaller than the global threshold T, then the image should be checked if it is globally blurry or not by computing the number of blocks with local variance values smaller than the threshold value t_2, where t_2=10. If there are more than 70% of such blocks than the image is identified as globally blurry one. Otherwise go to the step 4 from the part for computing the number of blocks with local variance values smaller than the threshold value t_1.

So, as one can see, we use three kinds of the thresholds in the algorithm. They are the global threshold T=60, and the local ones t_1 and t_2. Through extensive experiments we find that mostly the sharper image has a larger variance value. However, it is impossible to use only one fixed global threshold T for evaluating all the images since sometimes sharp images can have lower variance value like the blurry ones (for example the images with large smooth areas). The value 60 is such the variance value that usually globally blurry images do not overcome, but sharp and partially blurry images can have variances larger than 60 or smaller as well. Thus, to detect really sharp images from globally or partially blurry ones we need some additional criteria. They are the number of blocks with variance values smaller than t_1 or t_2. The threshold t_1 is obtained automatically from the image itself (see Step 3 in the proposed algorithm). As for the threshold t_2, we propose to take value 10 because mostly the sub-blocks of really blurry images have variance values in the range from 0 to about 5.0. But to be sure we put t_2=10. And if more than 70% of the blocks have such low values smaller than 10, then the image is identified as the globally blurry one.

V. Experiments

For the first experiment we take 140 photographs using a digital camera of spatial resolution 960x1280. Among them 70 images are realistically blurry, and the rest of them are sharp. For the second test, 200 color photographs of spatial resolution 1536x2048 are taken (almost all of them are sharp). To simulate their blurriness we add artificial blur to these images using Gaussian and motion filters with the same parameters of blurriness for all the images. An example of intentionally blurred 400 images and their

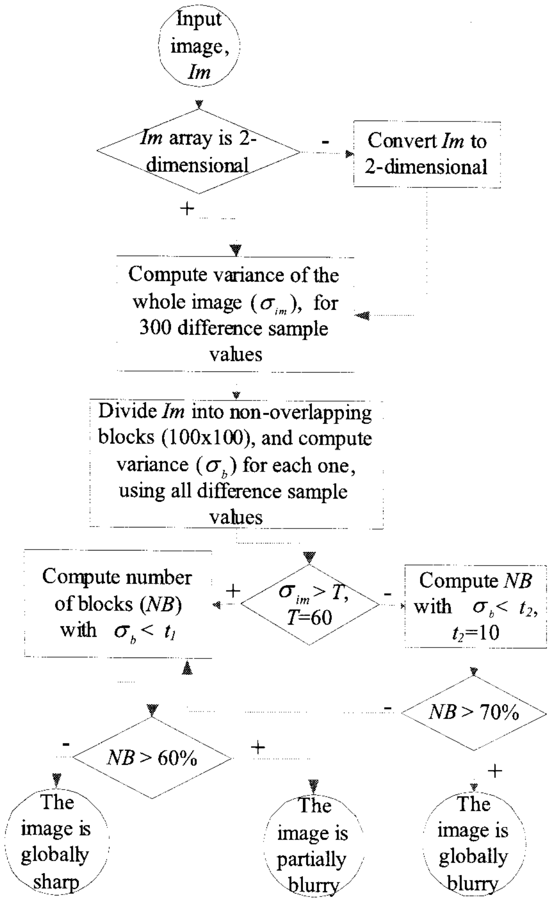

Fig. 5. Block scheme of the algorithm for the proposed method

original counterpart 200 images is shown in Figure 6.

As a result, we tested 740 images (140 images plus 200x3 images). In these experiments that use both sets of test images we compute variances (see Figure 7) with P = 300 sample pairs from $M \cdot (N-1)$ 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. However, unfortunately, the variance of the partially blurry one can infrequently be larger than sharp one as shown in Figure 7. Similarly, the variance value of sharp image can be relatively small. 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. That is why we propose to use additional criteria that allow users to detect globally blurry images from a pool of photographs taken by digital camera.

In other words, false alarm is inevitable. Motion-blurring is easier than Gaussian-blurring in this experiment since

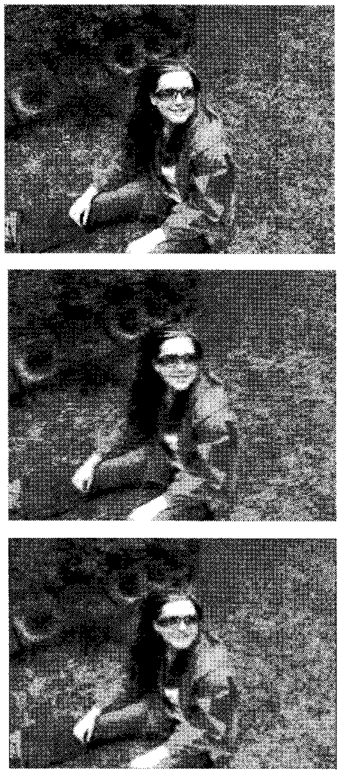

Fig. 6. Original image (top), motion-blurred image (center), and low-pass filtered image (bottom)

that variance is far smaller than this variance. If the degree of motion-blurring is insignificant, variance values will be closer to those of sharp images and visually such images will not differ much from sharp ones. However, the degree of motion-blurring by novice photographers is, in general,

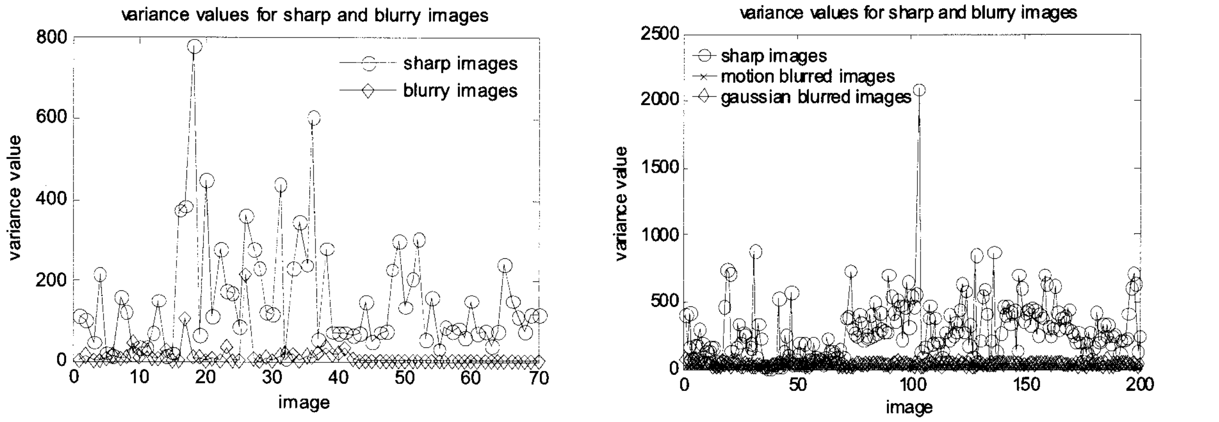

Fig. 7. Variances of 140 images (top) with 70 sharp ones and 70 blurry ones, those of 600 images (bottom) with 200 original, 200 motion-blurred, and 200 low-pass filtered ones computed using the proposed measure in this paper

more serious than that of this experiment.

As a conclusion, based on the proposed algorithm we detect 98.15% of sharp images (265 from 270 sharp images where 70 sharp images are taken from the first test and 200 images are taken from the second test).

The similar experiments have been done using the variance method[2] to compare results. We compare with this method because they also use variance values for evaluation images, but those values are obtained from the original images pixels'values, not from the difference between them. The original 200 images and blurred versions of them are used for the experiments (the same amount of blurriness has been added as for the previous test). As shown in Figure 8, note that the distance between circled line (for original images) and lines with crosses or diamonds (for blurred images) is very close compared with Figure 7.

As a conclusion, based on the proposed algorithm we detect 98.15% of sharp images (265 from 270 sharp images where 70 sharp images are taken from the first test and 200 images are taken from the second test).

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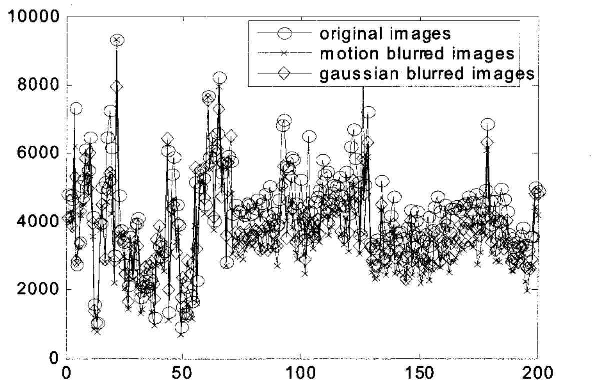

Fig. 8. Variances of 600 images with 200 original, 200 motion-blurred, and 200 low-passed filtered computed using [2]

Since the gap is very close, it is extremely difficult to tell good quality images from the bad ones. In this experiment, with method proposed in [2], we set the threshold value T to be 4,000 (as variances are obtained from another values than in our method). Then, among 197 original really sharp images, 122 are detected to be sharp images (see Table 2).

The same experiment has been done using the method proposed by S. Lim. This method in [3] outperforms the variance method[2]. The disadvantage of the method in [3] is highly computation-intensive procedure that uses some global measures obtained from local ones. However, these methods fail to beat the method proposed in this paper in terms of complexity and accuracy.

Table 2. Number of false alarms of three methods

Number of false alarms among 200 images	Ours	[2]	[3]
Sharp images declared as blurry	3	78	28
Motion-blurred images declared as sharp	0	50	18
Gaussian-blurred images declared as sharp	3	66	24

For additional experiments with our method we take 5 more sets of 200 color images in each. There are different kinds of photographs in these sets: really sharp, out-of-focus, images with small amount of exposure, motion blurred, noised images, etc. The resolutions of the photographs also vary: 960x1280, 1200x1600 or 1536x2048. With purpose to detect only really sharp images we got the results as shown in Table 3.

Table 3. Detection rate of sharp images for additional experiments

Number of set	Detection rate of sharp images
Set # 1	92.96%
Set # 2	94.41%
Set # 3	90.79%
Set # 4	93.79%
Set # 5	98.70%

Based on the experiments we can conclude that the proposed measure is very simple and efficient. Unfortunately, there are images that induce wrong decision. Example images inducing misses for sharp images or false alarms in blurred images with the proposed measure are shown in Figure 9.

Totally, in our experiments we used more than 3,500 color digital images (1340 original images and their blurred variants), and the average detection accuracy of sharp images is 93,5%.

Fig. 9. Sample images that cause false alarm or missing with the proposed measure

VI. Discussions and Conclusion

It is worthwhile to point out that the notion of sharpness depends on the situation and an observer [3]. Sometimes people intentionally take pictures with intrinsically untextured objects such as snow or sky. We also take partially blurry pictures by adjusting depth of focus for special effects such as a photo of bees on little blurry petals. Thus, it is difficult to give a golden rule that perfectly discriminates good and bad images. Although the points of view may be subjective, blurriness/sharpness measures are necessary for modern digital imaging devices. Even though, recently, many digital cameras are equipped with various autofocusing functions, however, the effect of blurriness still occurs sometimes.

The proposed measure is fast, simple and efficient. Only Psample pairs are used for computing the measure among $M \cdot (N-1)$ sample population. In this paper, the main target of this measure is detecting really sharp photos from a pool of digital photographs. Needless to say, this measure can be used for various imaging applications including autofocusing and astigmatism correction.

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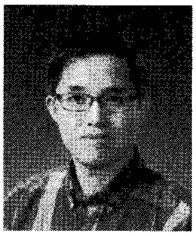

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