Automatic Blurry Pictures Deletion Tool for Digital Cameras

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Abstract

In this paper we present a new simple and efficient method for real-time automatic detecting and deleting blurry pictures while they are stored in digital cameras. Recently, many digital cameras are equipped with auto-focusing and motion compensation functions to help the users take well-focused pictures. However, digital images can be degraded by limited contrast, inappropriate exposure, imperfection of autofocusing or motion compensating devices, limited knowledge of amateur photographers, and so on. In order to detect blurry images immediately after taking the pictures by digital cameras and delete them a reliable tool for image quality estimation is needed. This paper presents a new tool for automatic blurry pictures detection and deletion in digital cameras. The main conception used for this tool is the ratio value between a pre- and original images. The algorithm is also based on the prediction-error variance, and demonstrates its feasibility by using extensive experiments. This method is fast, easy to implement and accurate. Regardless of the detection accuracy, the proposed tool in this paper is not demanding on computation time.

1 Introduction

Since the technology developed and digital cameras appeared in the market the measures of sharpness become a challenging problem among the developers of digital technologies. Also various methods for image quality estimation have been proposed in many engineering and scientific applications including the autofocusing in digital cameras, and astigmatism correction in the scanning electron microscope or the transmission electron microscope [5]. Nowadays, with high-quality digital cameras users can take hundreds of pictures a day. However, for some reasons they still can get low quality images (e,g, motion blurred, out-of-focus, etc.) and it is not easy for them to look through all their pictures to decide which of them can be deleted (for example, if the storage is full), or which of them should be taken for an enhancement process. Thus, they need some tools that would automatically detect and delete the low quality images. The main objective of this paper is to automatically detect globally blurry images and further delete them from digital camera storage. Typical causes of blurriness include: loss of focus, camera jitter, moving objects, limited contrast, inappropriate exposure, and so on. However, imperfect focusing and/or motion are the main source of blurriness in digital photographs. In this context, the algorithm for blurriness detection takes the Gaussian and motion blurriness into consideration.

In order to automatically select blurry pictures among a pool of digital pictures, various measures of sharpness or blurriness have recently been proposed in [1], [3], [4], [7], [9], [10]-[14]. The simplest measure is the ratio of high frequency components to low frequency components.

Blurry pictures may have smaller gradients in the edge regions and less energy in high frequency components. Thus, images are usually transformed by the DCT or the DWT, and are quantized to see how many high frequency components exist [6], [8]. Batten et al. [2] evaluated the variance measure and concluded that it is better than others in terms of computing time and immunity to noise.

Lim et al. [7] have developed an effective and efficient algorithm which uses several global figure-of-merits computed from the local image statistics. Thus, one can see that there already exist some methods for image quality estimation. However, most of them are time-consuming, computation-intensive, need different kinds of transformations (e.g., DCT or DWT), or the detection ratio is not very high.

In this paper, we propose a new tool for automatic real-time detection and deletion blurry images from digital cameras. The algorithm is based on computing the ratio of variance values between the pre- and original images. In other methods they estimate all the taken images themselves, however in the proposed method we do not estimate images' quality but only compute the ratio of the pre- and original taken images, which allows to save time significantly. For this method, no transform is needed. No complex and time-consuming operation is requested. Computing the prediction residue for P sample pairs and computing the ratio of variance values are sufficient. In addition, the accuracy of the proposed technique is very high. This paper shows why the algorithm of the proposed tool is mathematically reliable, easy to implement, and fast. In

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addition, the feasibility of the proposed method is shown with thorough experiments with various images.

Further, the paper is organized as follows: Section 2 provides the theoretical background of the proposed tool which includes the description of the prediction-error variance in 2.1 and the algorithm itself in 2.2; experiments are described in section 3, and discussions and conclusion are given in section 4.

2 Theoretical Background

2.1 Prediction-Error Variance

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 simplest predictor for an image is the one that uses the previous pixel, $u(x, y-1)$, in the image as the predicted value, (x, y), of the current pixel, $u(x, y)$. In this case, the prediction residue, $g(x, y)$ is nothing but the difference between the adjacent pixels. Hence, $g(x, y) = u(x, y) - u(x, y-1)$.

Figure 1 shows the original Baboon image and its motion and Gaussian blurred counterparts, respectively. And Figure 2 shows the histogram of the differences between adjacent pixels for the original Baboon image (solid line) and, for example, its Gaussian blurred version (dashed line). The standard deviations of these pictures are 184.4 and 1.60, respectively (see Table 2.1). In order to compute these values we took all the difference values of the neighboring pixels. However, to decrease the computational intensity for the proposed method only 300 samples were taken randomly, and experiments show that we can also rely on these variables' values as well (compare Tables 2.1 and 2.1). The variance values are computed by Equation 1 and Equation 2 that are given as follows:

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

$$S_p^2 = \frac{1}{P-1} \sum_{k=1}^{P} [v(k) - \bar{v}]^2, \qquad (2)$$

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

The sample variance value in Equation (2) is computed using P sample values. We randomly select P difference values from the two-dimensional array $g(x, y)$ and allocate them to the one-dimensional array, $v(k), k = 1, ..., P$.

Figure 1: Example of the original Baboon image (left), and its Gaussian (center) and motion blurred (right) versions, respectively

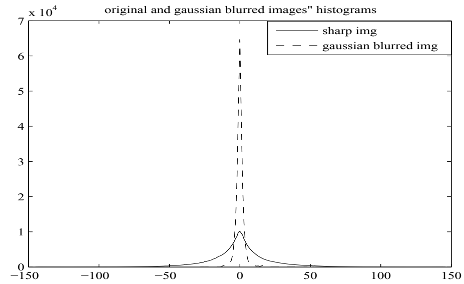

Figure 2: Distribution of prediction residues of the original Baboon image (solid line) and its Gaussian blurred image (dashed line)

Images	S_p^2 of sharp image	S_p^2 of blurred image
Bicycle	634.34	3.51
Fish	152.86	2.28
Baboon	158.06	1.55
Mandrill	42.28	0.84
Birds	31.64	0.80
Lena	71.66	1.47

Table 1: Variances of a set of standard test images: sharp ones and their blurred counterparts (for 300 random samples)

Images	S_p^2 of sharp image	S_p^2 of blurred image
Bicycle	587.7	3.49
Fish	155.6	2.48
Baboon	184.4	1.60
Mandrill	37.8	0.85
Birds	28.0	0.89
Lena	49.3	1.40

Table 2: Variances of a set of standard test images: sharp ones and their blurred counterparts (for all the difference values)

2.2 Algorithm

The core of the proposed algorithm is the ratio of sample variance values between the pre-image and the original taken image. We assume that before full pressing the shutter button in order to capture a picture (i.e. when the button is half-pressed), a digital camera keeps this auto-focused image in the internal memory. And we define this image as a "pre-image". This pre-image we use to compare it with the actual taken image that is saved in the external memory after full pressing the shutter button. If the ratio (3) of their sample variance values is approximately equals to one or less than one (i.e. $R \approx 1$ or $R < 1$), then we conclude that the taken image is the same as automatically well-focused pre-image or the auto-focused image's quality is lower than the one of the actual taken image:

$$R = \frac{S_{p1}^2}{S_{p2}^2}, \tag{3}$$

where S_{p1}^2 stands for sample variance value of the pre-image and S_{p2}^2 stands for sample variance value of the taken image.

Otherwise, if $R \gg 1$, then, while taking a picture some distortion had happened to it (e.g. object moved, or camera was shaken, etc.) and, thus, the taken image is possibly blurry. After having look at this image at the display of digital camera user decides whether to delete this image or not.

As a preprocessing, in the proposed tool we only need to convert the input images from RGB colors to grey-level luminance values. The algorithm for the proposed tool is shown through the flowchart in Figure 3.

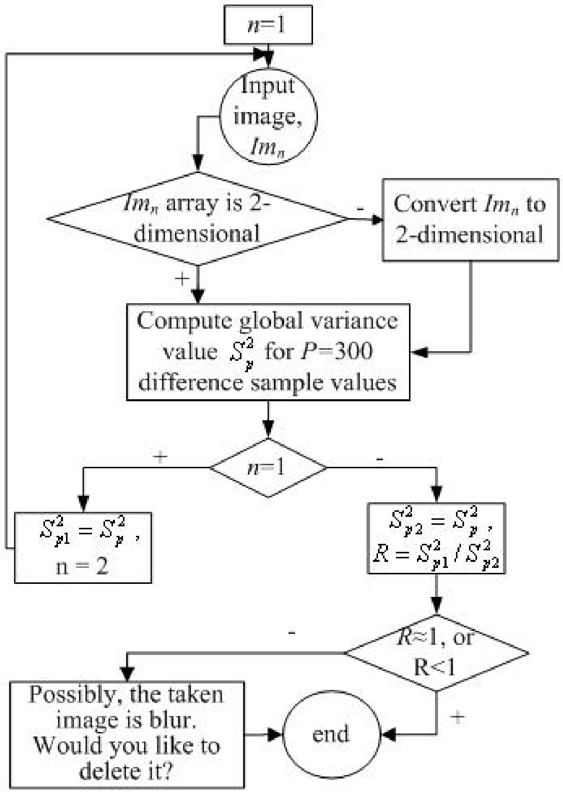

Figure 3: Block scheme of the algorithm for the proposed tool

3 Experiments

Our new tool is proposed after previous extensive experiments on images' quality estimation. In those experiments we evaluated all the images in order to separate them into three categories: globally sharp, average quality and globally blurry. Now we simplified that technique in order to apply it for automatic real-time in-camera blurry pictures detection and deletion. Below, we briefly describe results of the previous experiments in order to show that sample variance values used for computing the ratios are reliable in the proposed new tool.

For first our experiments we take only 200 digital photographs and later four more sets with 200 photographs in each one are taken additionally by different digital cameras (e.g. Nikon, Canon, Samsung, Sony). There are different kinds of photographs in these sets: globally sharp, out-of-focus, images with insufficient exposure, motion blurred, noised images, etc. The resolutions of photographs also vary: 960×1280, 1200×1600, or 1536×2048, the most common among general users. The contents in the Set ♯1 to Set ♯4 are a potpourri of outdoor, indoor, landscape, far, close, building photos, and so on. After comparing performance of our prediction-error variance blurriness/sharpness detection technique with the methods proposed in [5] and [7] we found that our method produced quite good results.

Table 3 shows that our method produces a very low false alarm rate compared to other methods. And Table 3 shows that the detection ratio of our method is very high.

As for the ratios of variance values between the pre- and original images, they are increasing with increasing the amount of blurriness in taken images. Before, in theoretical background section, we showed that, for example, Baboon image has sample variance value 158.06 for sharp image and

1.55 for the blurred one (see Table 2.1). Let assume that the sharp image is a pre-image, stored in a digital camera after half pressing the shutter button, and the blurred image is the actual taken image after full pressing the shutter button. Then, the ratio of their variance values is 158.06/1.55, i.e. 101.97, that is much more than one, i.e. $R \gg 1$. It means that the taken image is globally blurry.

In Figure 4 we show that with increasing the parameters of blurriness of digital images, their sample variance values are going down. $MB1 - MB5$, and $GB1 - GB5$ mean from the first Motion Blurred image ($MB1$) to the fifth Motion Blurred image($MB5$), and from the first Gaussian Blurred image ($GB1$) to the fifth Gaussian Blurred image ($GB5$), respectively.

Just for giving an example we take 5 globally sharp images from our database and apply motion and Gaussian blurriness to them with different parameters. We implemented it in four steps in order to get variances of the images from slightly to significantly blurry ones. LEN and $THETA$ parameters for motion blurring are taken as following: step 1 - (7, 1), step 2 - (13, 2), step 3 - (19, 3), and step 4 - (25, 4). For the gaussian blurriness the $HSIZE$ and $SIGMA$ parameters are taken as following: step 1 - (5, 3), step 2 - (10, 6), step 3 - (20, 9), and step 4 - (31, 11). Thus, from the Figure 4 one can see that the sample variance values of the images are dropping down significantly with increasing the parameters of their blurriness, regardless of what kind of blurriness they have.

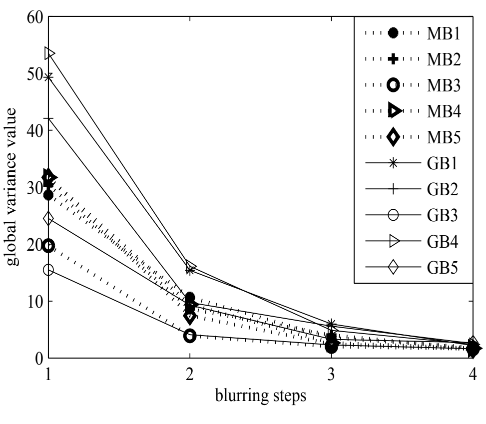

Figure 4: Variance values of the motion and gaussian blurred images (MB and GB, respectively) with different parameters of the blurriness in each step

Number of false alarms among 200 images	Ours	[5]	[7]
Sharp images declared to be blurry	3	78	28
MB images declared to be sharp	0	50	18
GB images declared to be sharp	0	66	24

Table 3: Number of false alarms of three methods

Image set	Detection rate	Image description
Set #1	100.0%	Outdoor, people
Set #2	100.0%	Outdoor, landscapes, views of city
Set #3	93.8%	Indoor, at party, at dinner
Set #4	98.8%	Outdoor, at concert

Table 4: Detection rate of globally blurry images for additional experiments

4 Discussions and conclusion

It is worthwhile to point out that the notion of sharpness depends on the situation and an observer [7]. Sometimes people intentionally take pictures with intrinsically untextured objects such as snow or sky. We also take partially blurry pictures by adjusting the 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, since the average quality images exist as well. Although the points of view may be subjective, blurriness/sharpness metrics are necessary for modern digital imaging devices. Even though, recently, many digital cameras are equipped with various auto-focusing and motion compensating functions, blurry pictures are unavoidable.

The proposed blurry pictures detection and deletion tool is fast, simple and efficient. Only P random sample pairs are used for computing the measure among an $M \times (N-1)$ sample population. No thresholds, no transforms, and no division of images into non-overlapping subblocks are required. Every decision is made based on the ratio of global sample variance values between a pre- and original images. In this paper, the main target of the proposed algorithm is to detect the globally blurry images and delete them from digital camera storage so that it will allow saving amount of external memory, deleting unnecessary low quality images.

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