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Generating Blurred Dataset with Different Blurriness Degree Variances

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ABSTRACT: Many researchers in image and video processing field test the effectiveness of the proposed or existing methods depended on the assumption that the brightness or illumination in scene is static among all sequenced images or frames. So they used synthetic dataset with frames contain approximately static blurriness degrees. This is not practical in the real world. In this paper, a method of generating synthetic blurred video dataset with frames containing different blur variances to solve this problem. The result showed that the proposed algorithm has ability to produce useful blurred dataset with having different blurriness values.

KEYWORDS: Blur, synthetic dataset, random number generator, averaging filter.

1 INTRODUCTION

In real-time application such as video surveillance especially, atmospheric changes are natural phenomenon which causes degradation of the quality of images or videos. The results of degradation are blurry or noisy videos. When surveillance camera captures video sequence for a certain area under different illumination conditions, the contrast and color of video frames are altered or degraded and the visual quality score will be different among all frames in the sequence.

General blurs and noise are the most common artifacts in images or video sequence recorded by a camera. Image blurs caused by many sources, such as camera shake, moving objects, and illumination variation in a scene [1]. Some time, possibly some frames are exposed to blur or noise.

The availability of data is very important for testing and evaluating algorithms [2]. In some situations, the data is difficult to obtain, synthetic data is alternative to simulate the real one. Recently, there are many synthetic realistic image and video generation techniques for testing the proposed or existing approaches have been proposed in in many different fields. Although in each field the requirement of generating synthetic data are different.

Rodrigues et al. proposed a method to evaluate data fusion based on realistic synthetic satellite images that were generated using Gaussian filter and averaging techniques [3]. Al-Musawi and Hasson proposed a method to generate synthetic video streams for video summarization. The proposed method generates synthetic distorted video stream using Gaussian noise generator for dynamic scenes [4]. Vougioukas et al. presented a method for restoring the blurry video underwater recordings obtained from surveillance cameras. They proposed to use of good quality frames from the beginning of the video sequence that do not yet contain the blurs in order to restore the next frames back to their original quality. A few good quality frames corrupted using a Gaussian blur was used to improve the proposed method [5]. Rezatofighi et al. presented a framework which uses simulation of the image formation process and accurate measurement for generating realistic synthetic sequences of total internal reflection luminescence microscope with different quality [6]. Baheti et al. Proposed method for virtual focus and object depth estimation from defocused video. This defocused video was blurred by a simulated Gaussian blur [7]. Zhang and Jianchao presented a method to produce synthetic blurry video using changing motion parameter of a sharp image. In addition, Gaussian noise with standard derivation of 2 was added to each video frame. The generated blurry videos were used to improve the performance of video deblurring method [8]. Mokhayer et al. proposed a method to generate multiple synthetic face images from each single original face image to deal with illumination variations in order to improve recognition performance [13].

Most of the video processing methods for a single static camera or multi-camera video do not take into account to illumination changes which are occurred in some of video frames in a randomly manner. They depended on the assumption that blur or illumination values are static along video frames. In this paper, the proposed blur algorithm is presented in order to generate synthetic blurred video sequence containing frames with different blur variances.

2 BLURRING-LINEAR FILTER

Blurring or smoothing technique transforms an image to smoothed image by reducing the rapid variation between pixels in gray levels. The blurring process is achieved by computing the average of the pixels of the filter mask and then replacing every pixel value from the image by the average value. The output image is a new image with smoothed edges [11].

Averaging filter is used as a kernel convolved with all pixels of image. This filter was considered as low-pass filter eliminating edges and regions that have sudden grey-level change. For more smoothing, larger masks are used. Fig. 1 (a) shows standard average kernel for a (3 × 3) neighborhood region, and (b) shows a general $(n \times n)$ kernel or mask [9].

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix} \quad \frac{1}{n^2}\begin{bmatrix}1 & 1 & \dots 1\\1 & 1 & \dots 1\\\vdots & \vdots & \ddots \vdots\\1 & 1 & \dots 1\end{bmatrix}$$

(a) (b)

Fig. 1 (a and b) Standard and general average mask.

The averaging kernel mask can be represented as:

$$Avrage = \frac{1}{9}\sum_{i=1}^{9} f_i \qquad (1)$$

The $Avrage$ is the average of the gray levels of the pixels in the (3x3) neighborhood. This kernel is called a box filter when its coefficients are equal.

Convolution operation is a method of multiplying two array of pixels that are different sizes and the same two dimension. The result of this operation is an array of pixel of the same dimension. One of the input array is 2D image array of size $M \times N$ pixels and the second input array is a kernel (K) of size $m \times n$ pixels. The output image (OIM) has a size equals $(M - m + 1, N - n + 1)$ pixels. The convolution operation can be defined as [10]:

$$OIM(i,j) = \sum_{k=1}^{m}\sum_{l=1}^{n} K(k,l) * IM(i+k-1, j+l-1)\ , \qquad (2)$$

Where $OIM(i,j)$ is the output image at location (i,j) and IM is the original image.

3 PROPOSED METHOD

The nature of environmental conditions are variant in time, the blurring values are also variant in time. Therefore, in order to simulate the real blurred video sequence with dynamic blurring model among all frames in video sequence, a dynamic blurring generation algorithm has been proposed. The suggested blurring equation in Eq. (3) is computed by dividing the selected filter mask (box filter) on the random number generator function $(Randn(1))$. The final proposed mask is defined in Eq. (4) which is used in the convolution operation with the original data. The formulation of the proposed blur mask can be defined as follows:

$$\boldsymbol{Mask} = \frac{\frac{1}{9}}{\boldsymbol{Randn}(1)}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix} \qquad (3)$$

$$\boldsymbol{Mask} = \frac{\mathbf{1}}{(9)(\boldsymbol{Randn}(1))}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix} \qquad (4)$$

The final equation is obtained by convolution between the proposed mask and the original frame pixel $f(x,y)$ in video sequence:

$$f_{blurr}(x,y) = \sum_{k=1}^{r}\ \sum_{l=1}^{c} Mask(k,l) * f(x-k, y-l) \qquad (5)$$

Where , f_{blurr} is a blurred frame pixel, $(r \times c)$ is the size of the Mask window. The bigger in the size of the rectangular neighborhood window, the result will be more blurring. For example, for window of the size $(3 \ \times 3)$, the result is slightly blurred, while window of the size $(5 \ \times 5)$, the result will be more blurring. The algorithm (1) illustrates this operation.

$\underline{\boldsymbol{Algorithm}\ (\mathbf{1}): \boldsymbol{blurring\ modeling}}$

Input: Vid: $the\ original\ video\ sequence$

n: $the\ number\ of\ frames\ in\ Vid$.

$\boldsymbol{Output}$: $video\ containing\ with\ blurring\ frames$

$\boldsymbol{Steps}$:

1. Given the input video sequence.
2. $for\ i = 1\ to\ n$
3. $Read\ the\ current\ frame\ f_i\ from\ Vid$
4. $Compute\ Mask = \frac{1}{(9)(Rand(1))}\ [1,1,1; 1,1,1; 1,1,1]$
5. $f_{blurr} = conv2(\ f_i\ , Mask)$
6. $store\ f_{blurr}\ in\ video\ file$
7. end

The output of this algorithm is a blurred video sequence with different blur variants. In other words, each frame in the video has a different score variants.

$randn()$ is MALAB function for generating random numbers with a Gaussian normal distribution. The output of $X = randn(d)$ is $d \times d$ matrix of normally distributed random numbers. In this paper, $d = 1$ is used in order to obtain one random number at each iteration in the loop of reading sequenced frames.

4 SIMULATION RESULTS

The performance of the proposed algorithm is tested on video sequence captured by a digital surveillance camera in the metro London scene. The sequence were captured in a frame rate of 25 fps and with a resolution of 320×240. The output of the algorithm is blurred video containing frames with non-linear or dynamic blur components. The blur metric which is used to measure the degree of blueness of each frame in the sequence is called no-reference perceptual blur metric presented in [12]. The result of this metric is in [0, 1]. The values that are ranged to 0 means sharp, while the values that are ranged to 1 means blur. As shown in Table (1) and Fig. 2 and 3 the degree of blueness of the original video, the blur video generated by the traditional method, and the blur video generated by the proposed method are compared.

(a)

(b)

(c)

Fig.2: The visual results of the traditional and the proposed blur methods, (a) is the original video, (b) traditional blurred video, and (c) is the proposed blurred video

Table 1: Comparison between of the classical synthetic blurred data and the proposed synthetic blurred data

Original Video	Normal Blur Video	Proposed Blur Video
0.3539	0.4646	0.4632
0.3611	0.4704	0.4527
0.3565	0.4677	0.3348
0.3538	0.4658	0.4361
0.3539	0.467	0.4511
0.3649	0.4728	0.4251
0.3568	0.4684	0.4604
0.3588	0.4689	0.4655
0.3556	0.4674	0.4323
0.3493	0.4629	0.39

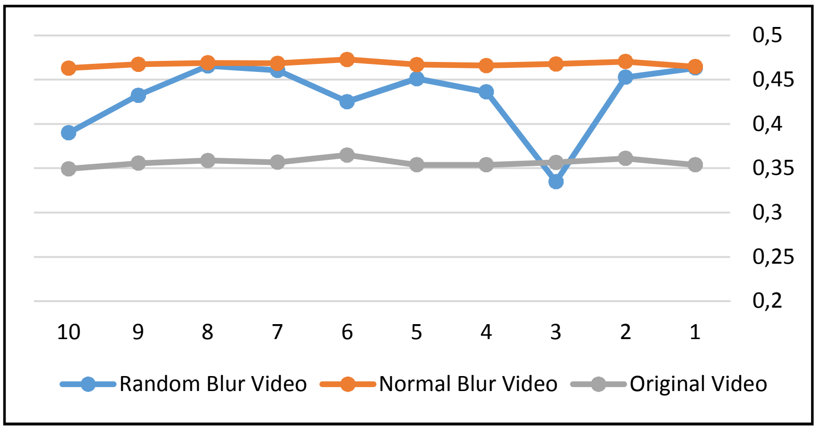

Fig.3 Graph of comparison between of the classical synthetic blurred data and the proposed synthetic blurred data.

From the table and the figure above, notice that the degree of blueness of the proposed synthetic blurred video have non-linear model, while the degree of blueness of the traditional synthetic blurred video has approximately linear model and almost looks like the original model. The benefit of the proposed algorithm is to generate synthetic blurred dataset to be available for the researcher in order to test their proposed algorithms instead using blurred dataset with static degree of blueness.

5 Conclusion

Many approaches in image or video processing test their methods on datasets that are approximately static or linear values of blurriness degree. In real world, the captured images or video sequences by digital camera have different blueness degree among frames. The proposed algorithm generate a video sequence containing frames have different blur variances. The proposed synthetic dataset could be beneficially employed in future works.

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