Smartphone Video Motion Deblur Modeled Based on Estimation Blur Parameter

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Abstract: many research approaches focus on image processing on smartphone platforms, visual object, augmented reality, object detection, tracking and recognition. sensor sizes are the main differences between camera smartphone and digital camera where sensor size is smaller in smartphone camera. image quality direct proportion with sensor size wherever the bigger get high quality. Most off smartphones featuring multiple cameras, multiple sensors in one device, but still none of them having large as digital camera. blur occur when there is relative motion between the camera and the object scene while capturing the image. blur, typically occur in low-light scenarios due to requiring exposures. lens blur doesn't change significantly all over the image while object motion is highly directional and changes abruptly depending on the objects. Paper present method deal with the main challenges occur in smartphone video platform. proposed method eliminates small motion blur in three phases. Blur estimation achieved by prior information on distribution image gradient. Orientation Gaussian Filter fit the prior information to find the regression coefficients. Multi order combine different estimate GOF parameters to generate removal blur filter. Estimation parameters are fix and set blur on the image to produce image without boosting the noise and unwanted artifacts. Proposed model generated images that have more details instead of directly minimize which is solve optimization problem by minimize loss function. Suggested method applies on outdoor, indoor video acquired by modern smartphone. Experiment result display is accurately for the full regression motion blur model. suggested model exam on video dataset conditions 23:75 sec, 229,44 MP. measurement evaluation established on time consumer, SSIM and PSNR. experimental results show image artifacts phase less consuming computational time. proposed model has minimized cost function and form image quality greater.

Keywords: Smartphone Platform, Motion Blur, Orientation Gaussian, Blur Filter

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1. Introduction

many research approaches focus on Computer vision area topics visual object, augmented reality, object detection, tracking and recognition. smartphone platforms video and image have specifics problems cause camera, the main a reason is sensors sizes which are smaller than digital camera sensor. Pictures acquired by smartphone have many problems one of them is motion blur. Almost, object or camera move during time capture of the source motion blur. Digital camera image has light more than image acquired by smartphone because a larger sensor can receive a larger amount of light. sometime blur can be the result of wrongly setting the camera focus or due to limited depth of field when a large camera aperture is used. In Smartphone image there's a certain amount of intrinsic blur due to the optics and time captured by the camera. blur is a highly complex regression due to many different sources cause different type of blur which is represented by different mathematical model. image deblurring is generate a high-quality image with clean sharp for given a blurred image. the goal is to recover a sharper version of the real original image by removing the blur.

In real world scenarios as shown in the top formula, an image is captured during a time window. A blurred image is in fact an integration of multi -image instances and sharp snapshots. Traditional blurring method handles this problem by apply a blur filter. A sharper version of the input blur image can be recovered through blur filter. proposed method focuses on regression motion blurring model using blurred and sharp pairs. ghosting artifacts avoided and energy function processed minimize with customized image processing algorithms.

This paper focus on the two goals deblur image with small blur, eliminate artifacts results platform smartphone. The proposed method consisted three phases: first estimates image blur treats small noise then, apply a improved blur estimation parameters blur filter and a final step remove undesirable artifacts that may have introduced during the improved blur estimation parameters.

the blur estimation parameters improved by combining gradient parameters. operator blur filter extended to three orders models in order to restoration image. image deblurring is an improved blur estimation parameters problem which is goal to recover the latent clean signal. model has been designed to remove small motion blur and minimize loss function to do denoising. estimates blur parameters method are simple implementing and avoid loss function in the case of unidimensional vectors. PSNR SSEM measurement evaluate restoration image compare with target image .

2. Related Work

image blur problem discussed in many papers for previous thirty decades. In the [1,2] by Dennis Gabor work to reverse the heat equation in order to improve the sharpness of an image and this is actually related to image deblurring. [3,4,5] regression methods for non-blind and blind combined priors' data and optimization energy function. in the paper [6,7] and the [8,9] used model regression, the space of high-quality images, and solve a restoration problem based on these two things. The common techniques is actually based on using large amount of data and then, apply deep training models to do restoration. in the papers [10,11] are using total variation. Later in the [12,13] and [14] latest tendency started design many other approach of modeling high quality signals by using wavelets or sparse representation and dictionaries. in the [15] extended other types of research that deal with leverage ideas from other domains, for example, trying to use image denoisers as priors as in red or plan-and-play methods. And more recently, trying to leverage like genetic models learned from data as good image priors, for example, using Generative Adversarial Network (GAN) or variation autoencoders or even diffusion models as priors. The model is present a different method that tried to solve this deep learning problem in very specific conditions.

3. Deblur Modeled Based on Estimation Blur Parameter

previous methods processed blur images revealing unseen image details. The proposed methods modeled priori information producing estimated image blur based on Gaussian Orientation Blur (GOF) filter (GOF) filter parameters modeled to satisfy variety light distribution. proposed model goals

1- remove small blur come from camera shake and lens aberration
2- generate a sharper image without introducing any new artifact, limitation might be unrealistic i.e. object movement, depth of field.
3- it should be able to run fast on smartphone platform.

proposed model goals would achieve on three steps:

3.1 BLUR ESTIMATION

Estimation bluer based on parametrize the space of possible blur.Gaussian Orientation Filter(GOF) run on small nose .GOF defined by three parameters(α,β,∂) where(∂) the main orientation of blur while (α,β) standard division at the both principle axis . these assumptions accepted for small blur

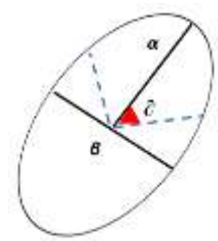
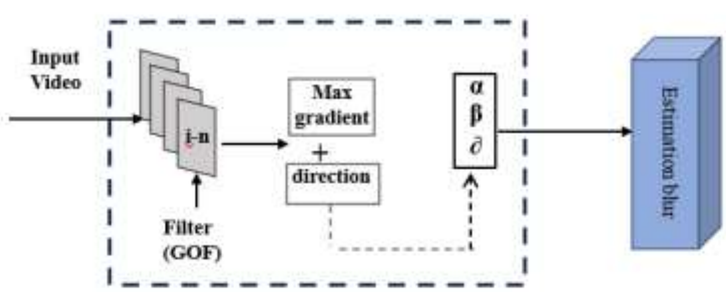


Fig .1 GOF parameters (α, β, ∂)

experiential target show that sharp images have roughly the identical maximum gradient intensity on all direction. The image gradient is related to the Gaussian blur standard deviation. The image gradient at different directions can identify which direction is the blurriest.

Fig.2 Blur Estimation



estimate the Gaussian parameters obtained from the maximum gradient values in that direction and orthogonal one as procedure below:

1-scan the gradient intensity at $\boldsymbol{N}$ different orientations

2- compute the maximum gradient value
$R\partial_{1,}R\partial_2 \ldots\ldots R\partial_N$

3- find minimum $R\partial$ determine the direction of the blur receptive to ∂ value

4- compute or estimate the standard deviation of the Gaussian blur filter

$$\boldsymbol{\gamma_1}=\sqrt{\frac{\mathbf{a^2}}{R^2\partial_1}-\mathbf{b^2}} \qquad \boldsymbol{\gamma_1}=\sqrt{\frac{\mathbf{a^2}}{R^2\partial_1}-\mathbf{b^2}} \;\ldots\ldots\ldots 1$$

3.2 Multi Order Model Improve Bluer Estimation

assumption small blur put on to estimate GOF parameters, to solve a problem of another blur type. paper proposed approach association different paraments of the blur to detect missing estimation blur. expand blur filter operator into three order when the blur is small, operator be close to the identity. General filter to remove noise as follow the equation:

$$v = uK + n \ldots\ldots\ldots\ldots(2)$$

Multi order filter add and subtract value of the estimated image blur. Multi order combine different estimate GOF parameters to improved estimation bluer .Multi Order model modified General filter to remove noise as follow the equation:

$$h(k)v = h(k)uK + h(k)n \ldots\ldots\ldots\ldots(3)$$

Where $h(k)$ equation:

$$h(k) = ak^2 + bk^2 + c\,k + dI \;\ldots\ldots\ldots..(4)$$

The coefficients (a, b, c) are set independently of the blur and image. The coefficients set to sense the blur without boosting the noise and unwanted artifacts. The model is going to force the reconstruction images to be in the divergent high-quality images.

3.3 Artifacts Detect and Removed

parameters that are extracted from the distribution of light gradient is appropriate high frequency information such as image sharpness. But using the distribution make this feature invariant to small shifts, noise and other small changes presented in images. Artifacts generate due to mis-estimation or due to operator model mismatch .the blur estimation is rough and the model might introduce artifacts which can be characterized as pixels have gradient reversal.

$$M(x) = -\nabla v(\mathrm{x}).\nabla u(x) \ldots\ldots\ldots\ldots\ldots(5)$$

the gradient on the reconstructed or de-blurred image references the opposite direction as in the input. Blurry image ($\boldsymbol{v}$) and restored image ($\boldsymbol{u}$) have opposite gradients, final image the reconstruction to avoid gradient reversal.

$$u_{Rinal}(x) = \alpha(x)u(x) + (1 - \alpha(x)v(x)) \ldots\ldots\ldots\ldots..(6)$$

Where

$$\alpha(x) = \frac{M(x)}{M(x)-\|v^2\|} \;\ldots\ldots\ldots\ldots..(7)$$

generate a merger filter that balances between the de-blurred image and the input image that minimize the gradient reversal. This allows to remove most of the sharpening artifacts. The model accepted for low and high quality imag. the parameters model satisfy minimize loss function. This loss function shows the mismatch between the prediction and the high-quality reference target. the square pixel reconstruction error compute directly to measure the variance in image pixels. images de-blurring do not have a unique solution. There is an infinite number of high-quality images that

can lead to the same low-quality target. To optimize minimize the loss function grounded the predict average of all possible solutions.
Through the best circumstances confirm minimize this error perfectly. predicted image dos not wholly de-blurry due to being the average of many possible candidates. apply blur filter through the sharpen feature and the integration to Photos

4. Experiment Results

experiments result present the analysis, evaluation and cost of the processing and implementation of motion deblur and noise removal based on estimation blur parameters. model implemented to eliminate small blur motion arise on smartphone video. dataset video are capture by smartphone platform witch specifications shown in table (1)

Table .1 smartphone specifications

DISPLAY	Type	Super Retina XDR OLED, 120Hz, HDR10
	Resolution	1170 x 2532 pixels, 19.5:9 ratio
	CPU	Hexa-core (2x3.23 GHz, 4x1.82 GHz)
	GPU	Apple GPU (5-core graphics)
MAIN CAMERA	Triple	12 MP, f/1.5, 26mm, 1.9µm, dual pixel PDAF, 12 MP, f/2.8, 77mm, 1.0µm, 3x optical zoom 12 MP, f/1.8, 13mm, 1.0µm 3D scanner (depth)
	Features	Dual-LED dual-tone flash, HDR photo
	Video	4K@24/30/60fps, 1080p@30/60/120/240fps, up to 60fps.

dataset designation to recover diverse motion blur situation where results obtained from examine different environment video as follow

scenario 1:

indoor in daytime: one object includes one moving object parallel with smartphone camera movement direction and both of them move slowly, global motion central

scenario 2

indoor in daytime: include two moving object and smartphone camera move fast in comparison of object move, both move in the same direction. local motion dominate in video, another shot tack for same object but object walk in front of static smartphone camera .

scenario 3

outdoor in daytime: include one object moving object parallel with smartphone camera movement direction. smartphone camera moves quickly facing an object so any change occur in image intensity results from the camera movement.

scenario 4

outdoor in nighttime: video includes one moving object and smartphone camera move in same direction but slowly than object moves.

scenario 5

outdoor in nighttime: include two objects move against smartphone camera direction and both of objects have slow move. Global motion dominates. Another sense fox in interfere of two objects .video split to 30 frame per second , the performance measured each phase individually compare blur frame with target.

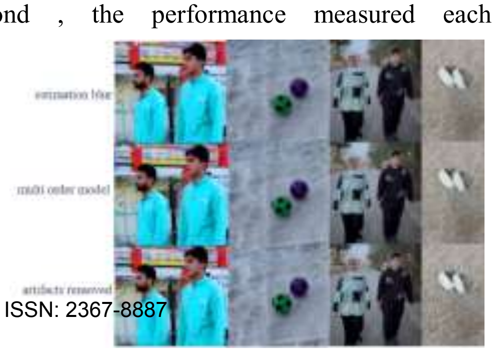


Fig. 3-a

Fig. 3-b

Fig.. 3 three phase deblur model match on different state of dataset outdoor and indoor in nighttime(a), daytime(b)

in general quality image measurement compare the content loss by estimations blur in frames. estimation adjusted to maximize parameters precisely which controlled blur detect from the low-quality input.
proposed method processes a 1MP frame in 230 ms using on a smartphone platform and time-consuming compute for deblur model phase individually. proposed de-blur model exam on variety of moving objects Each video reported the average of the results computed 10 times

Table. 2 time computing

Dataset	Blur Estimation	Multi Order Parameter Model	Removal Artifacts
Senrio1	66	13	9
Senrio2	203	94	14
Senrio3	235	35	16
Senrio4	61	19	3
Senrio5	152	75	20

estimation blur phase time expend bigger processing time than another phase. of course, the estimation needs less time according to different scene complexity . the main factor consuming time are camera movement rate and shining degree environment when acquired video. results compute average value to 30 fbs for each video. deblur model average process time a 8MP frame on a modern mobile platform in 300 ms.

frame quality characterizes sharpness of the restoration frame. distributed blur distance between model phase and target image. measurement PSNR and SSIM process frame data which depends on the previous step.

Table .3 PSNR computing

Dataset	Blur Estimation	Multi Order Parameter Model	Removal Artifacts
Senrio1	25.345	27.471	26.457
Senrio2	27.681	29.356	25.395
Senrio3	29.426	28.910	28.921
Senrio4	29.168	30.001	29.041
Senrio5	26.534	27.325	27.375

Table .4 SSIM computing

Dataset	Blur Estimation	Multi Order Parameter Model	Removal Artifacts
Senrio1	0.958	0.681	0.429
Senrio2	0.953	0.654	0.579
Senrio3	0.947	0.708	0.558
Senrio4	0.950	0.595	0.403
Senrio5	0.955	0.789	0.432

according to dominate type of motion wither global or local, obtained

deblur frame generate from three phase model. SSIM,PSNR indicate sharp grade after removal artifacts

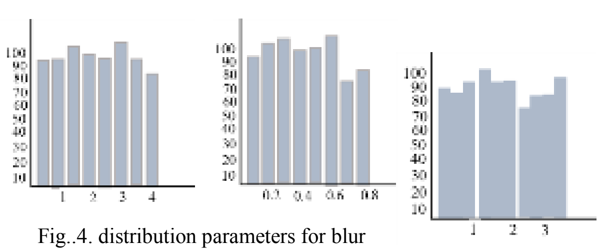


Fig..4. distribution parameters for blur estimation (α, , ∂)

Fig. .5-a Fig. .5-b

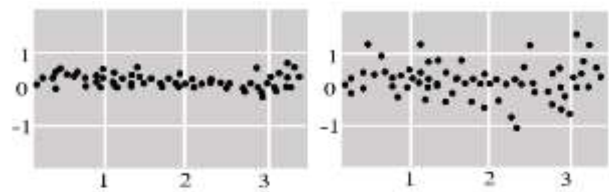


Fig..5. Blur model estimated error parameters (MES)

Parameters influence are c =9, σb =0.8 deblur filter apply to the input frame presents noise other artifacts. multi order apply with operator (α=5, b=2). small blur motion results are support .

greater visualization. multi order from the R3,α,b effect to Increasing α boosts small bluer frequencies high value coefficient (b) chiefs sharper frame .multi order can enhance bluer estimation result as a pre-step to eliminate artifacts. From compare the results table (2,3) find that (Removal Artifacts) phase dos not affected when process Blur Estimation accurately. scenarios have high value of PSNR,SSIM reduce process time about (50%), to get have process time for MPSA image size halved. Complexity quantity of estimation procedure is important factor effect on performance and motion of video .

5. Conclusion

Image deblurring is an improved blur estimation parameters problem which is goal to recover the hidden clean signal. modeling the variation of the gradient degree and direction in image. models in three orders to restoration image that minimize some loss function of the blur. blur estimation parameters coefficient improved deblur image that close to the identity blur, result move toward average of a low-degree. approximated model then processes image noise remain from filter.

. there is multiple high-quality signals that can lead to the same target image. this paper proposed solving improved blur estimation parameters problem is by variational formulation. variational formulation progresses an energy function that has multiple terms. optimization problem solved by the data fitting observable image and find compatible to the regression model

Accuracy of the deblur motion affected by the blur estimation, improved model and eliminate of artifacts detect and eliminate. PSNR and SSIM set to evaluate performance of proposed model for each phase

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