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Optimal Exposure Time for Image Restoration

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Abstract— Optimal exposure time for image restoration and an analysis of the achievable in calculating the maximum exposure time to take and reduce the motion blur and poissonian noise in a Image took by any kind of sensors. If the scene is suddenly took we can easily find out blur also if we take long time to take any scene we can see noise .The current softwares (like Photoshop) which are utilized to improve the quality of an image took by any kind of sensors. But we cannot find out the picture at what time it might take for capturing its original quality. So by finding the exposure time of a picture we come to know the quality of the picture. An analysis of the achievable restoration performance by showing the Optimal Exposure time from the image, Modeling Blur and noise using the mathematical formula and SNR- Signal to Noise ratio in the observation. A mathematical analysis of the signal-to-noise ratio in Fourier domain; this study is then validated by deblurring synthetic data as well as camera raw data.

Index Terms—Blur modeling, digital camera imaging, image restoration, noise modeling

INTRODUCTION

This correspondence concerns restoration from uniform motion blur, which is the blur produced by a convolution against a point-spread function (PSF) that is constant on its straight 1-D support. Uniform motion blur is a simplified description of the blur resulting from some translational motion between camera and scene during the exposure. Uniform motion blur has been considered in blind image restoration algorithms in the restoration of pictures containing moving objects the restoration performance varies when several uniform motion blurred images are available. Uniform motion blur seriously affects aerial images, and forward motion compensation (FMC) .Although uniform blur has been often considered in the literature, the blur and noise have been always considered independent whereas in practice they are always linked: e.g., by controlling the exposure time of a digital sensor, one can reduce the noise level at the expense of heavier blur, and vice versa. This correspondence aims at filling this gap, by introducing an image formation model that describes the interplay between noise, blur, and signal intensity as the exposure time varies. This model is particularly suited for the raw data from digital imaging sensors the proposed model allows to evaluate the tradeoff between noise and blur, aiming at establishing an optimal exposure time for which the image quality can be maximized by means of a deconvolation algorithm

IMAGE FORMATION MODEL

We model an image Z_T acquired with an exposure time T as

where $X \subseteq \mathbb{R}^2$ is the sampling grid and $\kappa > 0$ is a factor that can be used for scaling the signal into a usable (limited) dynamic range, thus, mimicking the amplification gain in digital sensors (typically, $\kappa \propto T^{-1}$). The two components $u_T(x)$ and $\eta(x)$ are independent random variables distributed as

$$u_T(x) \sim \mathcal{P}\left(\lambda \int_0^T y(x - vt)dt\right), \quad \eta(x) \sim \mathcal{N}(0, \sigma^2) \qquad (2)$$

where $\mathcal{P}$ and $\mathcal{N}$ denote, respectively, the Poisson and Gaussian distributions, and $\lambda > 0$ is a parameter characterizing the quantum efficiency of the sensor [9]. The function $y : \mathbb{R}^2 \to \mathbb{R}^+$ represents the original image while $v \in \mathbb{R}^2$ identifies the blur direction and velocity. The term η represents a source of noise that is independent from the original image y. In what follows, in order to simplify some derivations, we assume $0 < m \leq y \leq M < \infty$. This assumption is always satisfied in practical applications.

Original image

Let us now consider how the exposure time influences the signal-to- noise ratio (SNR) between the expectation of the observation (meant as the signal) and its noise. In order to clarify the interplay between blur and noise with the increase of the exposure time, we now reformulate the previously shown inequalities in Fourier domain. In what follows, for the sake of simplicity, we will consider discrete domain variables, ignoring possible aliasing effects in the convolutions.

$$\mathrm{SNR}\left(z_T(x)\right) = \frac{E\left\{z_T(x)\right\}}{\mathrm{std}\left\{z_T(x)\right\}} \asymp \sqrt{\lambda T} \underset{T \to +\infty}{\longrightarrow} +\infty.$$

Added blur with original Image

FOURIER DOMAIN ANALYSIS

The Fourier transform Z_T of the observation Z_T

can be expressed

$$Z_T(\omega) = \lambda\kappa Y(\omega) H_T(\omega) + S_T(\omega)\Theta(\omega)$$

Where(W)is a complex valued random variable with unit variance and zero mean, Y and H_T are the Fourier transforms of Y and H_T, respectively, and The SNR on each frequency allows us to speculate on the effects of both blur and noise in our observation

$$\mathrm{SNR}\left(Z_T(\omega)\right) = |Y(\omega)| \left[\frac{\lambda |H_T(\omega)|}{\sqrt{\sum_{x \in X} \lambda (y \circledast h_T)(x) + (\#X)\sigma^2}} \right]$$

$$\mathrm{SNR}\left(Z_T(\omega)\right) \leq \frac{\lambda |Y(\omega)|}{|\omega| \sqrt{(\#X)(\lambda c T + \sigma^2)}}, \quad \omega \neq 0.$$

I).Uniform Blur PSF

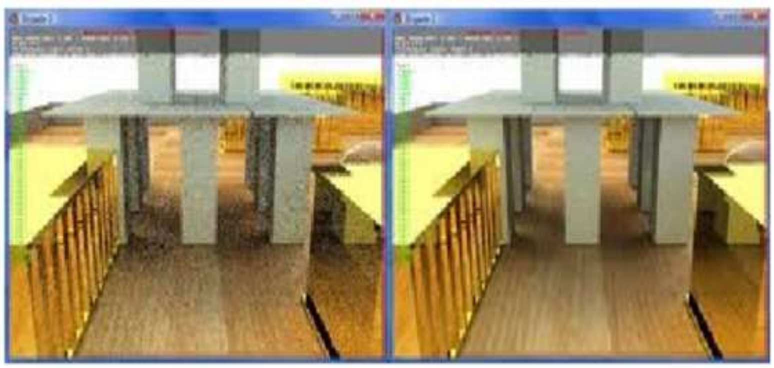
The blur is modeled as a linear and shift-invariant operator and, thus, using generalized functions, the argument of the Poissondistribution in (2) can be rewritten as

$$\lambda \int_0^T y(x - vt)dt = \lambda \int_0^T (y \circledast \delta_{vt})(x)dt$$
$$= \lambda \left(y \circledast \int_0^T \delta_{vt} dt \right)(x)$$
$$= \lambda (y \circledast h_T)(x).$$

II). Noise

Let us now consider how the exposure time influences the signal-to- noise ratio (SNR) between the expectation of the observation (meant as the signal) and its noise.

III). Obsevation SNR



I. Blur and Inversion

A quantitative estimate of the poor conditioning ilinear blur as the exposure time varies. Regardless of the particular technique utilized for recovering Yout of Z the inversion of the blur shall aim at scaling the attenuated spectral components. Effective debluring techniques are essentially non diagonal operators as they exploit the existing structural correlation in the under lying image Y to restrain the noise. The SNR of non-DC components of the restored image will, as T grows, necessarily decrease unless more and more correlations are exploited as a result of some kind of filtering

II. Optimal Exposure Time

From the equations derived so far we can conclude that, in case of uniform blur, increasing the exposure time may not result in observations that are easier to restore, as the conditioning of the blur operator may worsen. In particular, for each individual nonzero frequency, the corresponding SNR is inevitably maximized at a finite exposure time. In principle, this does not have any direct implication on the overall Quality of the restored image because such exposure times must not be the same for every frequency and more over each frequency SNR (Z_T(w))depends upon the image spectrum Y(w)

EXPERIMENTS

In this section, we show how the restoration performance varies with the exposure time, first by considering a dataset of synthetically blurred and noisy observation, and second by restoring blurred and noisy raw- data images acquired with a digital camera.

I. Deblurring of Synthetic Data

We synthetically generate several blurred and noisy observations according to five standard 512 X 512 grayscale test images (Lena, Hill, Boats, Baboon, Man), by considering 100 exposure times exponentially distributed between T_1=.005 and T_{100}=1. The test images are normalized so that black and white correspond to 0 and 1, respectively.

II. Deblurring of Camera Raw Data

In order to ensure uniform motion blur, we acquired a sequence of pictures in front of a monitor running a short movie in order to provide a ground-truth image for measuring the restoration performance.

Conclusion

We presented an image formation model where both the blur due to camera motion and the sensor noise are defined as functions of the exposure time. This model can be directly generalized to arbitrary motion PSFs and it based upon blurred/noisy image pairs as it offers a unified description of both long-exposure and short- exposure images. On our study highlights that there is a finite optimal exposure time which maximizes the restoration performance, balancing the blur/noise tradeoff in the observation. According to experiments on both synthetically generated observation and on camera raw data, the estimated optimal exposure times correspond to observations that are corrupted by noise levels that are far form being negligible. Thus, at least in case of uniform motion blur, explicitly handling the noise long- becomes a mandatory issue for algorithms that rely on observations acquired with varying exposure times.

References

1. Rav-Acha and S. Peleg, “Restoration of multiple images with motion blur in different directions,” in Proc. 5th IEEE Workshop Appl
2. Uniform Motion Blur in Poissonian Noise: Blur/Noise Tradeoff Giacomo Boracchi and Alessandro Foi