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Simulating motion blur and exposure time and evaluating its effect on image quality

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Abstract

Capturing images under low light conditions generally results in loss of contrast and difficulty discerning objects for both human observers and machine vision systems. To address this, the gain and exposure time are often increased to brighten the image. This may lead to the images becoming heavily affected by noise or motion blur. The impact of motion blur on image quality is therefore an important consideration. We present a simulation in which the exposure time and motion blur can be simulated and the impact on image quality metrics can be measured. Traditional image quality metrics are investigated, as well as some recently-proposed alternatives. Our simulation incorporates the exposure time, motion blurring, camera setting, ambient lighting, a noise model, and optical blurring. The model allows the blurring of image quality targets and real-world images; in this paper, image quality targets are used. The variation in image quality as a function of motion and exposure time may be useful in system design, in particular, determining the sensitivity to relative motion between object and imaging system.

Introduction

The occurrence of motion blur in an image arises from the relative movement between the image acquisition system and the object during the exposure window. It is known that motion blur has a significant impact on image quality and object detection performance, particularly in the context of autonomous vehicles. In low-light conditions, the diminished illumination of the environment can lead to less contrast and discernible information in the images, requiring an increase in exposure time and/or gain to enhance image quality. However, merely increasing the gain will only amplify what is already captured, including noise, without improving the signal-to-noise ratio. Increasing exposure time, on the other hand, increases the amount of information captured but will also increase the noise. The optimal exposure time for a given application remains a challenge. The conventional approach to investigating these trade-offs typically involves mathematical calculations, assumptions, and iterative trials. A controlled simulation approach, on the other hand, provides the advantage of controlling and measuring the variables of the scene, which can be difficult to achieve in real-world scenarios. Utilizing a simulation will enable the definition of the limits of the camera and algorithm under investigation, and ultimately determine the range of exposure time and motion blur for a specific camera application that will produce a target performance level. The objective of this paper is to investigate the relationship between motion blur, exposure time, and image quality metric values. The results may be used to define a range of tolerable exposure times and motion blur for a given camera application.

Image Quality Metrics	Units
SNR	dB
MTF50	Cycles per pixel
SIC	Bits per pixel
NEQ	Photons

Table 1: Image quality metrics used and the corresponding units

Related Works

Motion blur

As previously mentioned, motion blur is a common issue in autonomous vehicle applications. The problem is further amplified under low light conditions, where the exposure time is increased. Many studies have shown that blur has a significant impact on image quality and object detection performance, both of which are crucial in an autonomous vehicle application [1, 2, 3, 4]. Dodge et al [2] showed that CNN performance, while resilient to artifacts and contrast, is very susceptible to blur and noise. However, many of these studies simulate blur using Gaussian statistics and do not explicitly simulate motion blur.

Metrics

In optics, the most common image quality metrics are Modular Transfer Function (MTF) and Signal to Noise Ratio (SNR). Both MTF [5, 6] and SNR [7] are very well-established metrics. In recent years, these metrics alone have been considered to be insufficient for the quantification of the performance of modern-day image applications, especially when trying to relate image quality back to object detection performance. Recently, newer metrics such as Shannon Information Capacity (SIC) [8] and Noise Equivalent Quanta (NEQ) [9] have gained popularity in the image quality community. Both of these metrics are combinations of signal and noise components. A list of the metrics used and its corresponding units are shown in Table 1.

MTF and SNR

$$C(f) = \frac{V_{max} - V_{min}}{V_{max} + V_{min}} \tag{1}$$

$$MTF(f) = 100\% * \frac{C(f)}{C(0)} \tag{2}$$

In optics, the difference between bright and dark is referred to as contrast [6]. The amount of contrast that is preserved by an imaging system, as a function of spatial frequency, is captured by the Modulation Transfer Function (MTF). MTF is a key metric used to measure sharpness[5]. The calculation of MTF and sine pattern contrast (C(f)) at a spatial frequency (f) and luminance (V) is shown in Equation (1) and Equation (2) [10]. The most commonly used point on the MTF curve is the point where the contrast decays to 50% of its low-frequency values, more commonly called MTF50. The signal-to-noise ratio (SNR) is a well-known measure that compares the level of a desired signal to the level of background noise [7].

Shannon Information Capacity (SIC)

Traditionally, SIC [8, 11] is a widely used quantity in communication systems and information theory and defines the maximum rate in bits per second that data can be transmitted through a channel without error. From an image quality perspective, a camera can be viewed as a "channel". Hence, SIC measures the maximum information that an image can contain. As shown in Equation (3) [8], SIC is a metric that combines both signal and noise in its calculations. S(f) is the signal component, N(f) is the noise component and B is the Nyquist frequency.

$$SIC = 2\pi \int_0^B logs_2\left(\frac{S(f)+N(f)}{N(f)}\right) f df \tag{3}$$

Noise Equivalent Quanta (NEQ)

As shown in Equation (4), NEQ combines both MTF and Noise Power Spectrum (NPS) to quantify the square of the signal-to-noise ratio (SNR) as a function of spatial frequency [8, 9]. In Equation (4), μ is the mean linear signal and v is the spatial frequency.

$$NEQ(v_x, v_y) = \frac{MTF^2(v_x, v_y)}{NPS(v_x, v_y)/\mu} \tag{4}$$

Methodology

Target Charts

The target chart used for the work described in this paper is the Siemens Star chart [12]. The Siemens Star chart measures MTF from a star pattern along the radii of a circle for a range of angles. This chart is scale-invariant, measures MTF in a variety of angles, and has the benefit of noise and signal being measured in the same location. The alternative to the Siemens Star chart is the slanted edge chart [13]. The slanted edge may be favorable in many cases due to its robustness but in the use case for this paper, the Siemens Star chart was used for its ability to measure MTF from a variety of angles [14, 15, 16].

Simulation flow

In Figure 1, we have shown the flowchart of the simulation. The camera configurations that are used include the quantum efficiency, sensitivity, baseline offset, and bit depth of the camera. The number of electrons generated by photons hitting an active area of the sensor is obtained from the quantum efficiency. The sensitivity of the camera represents the amplification of the voltage in pixels from the photoelectrons.

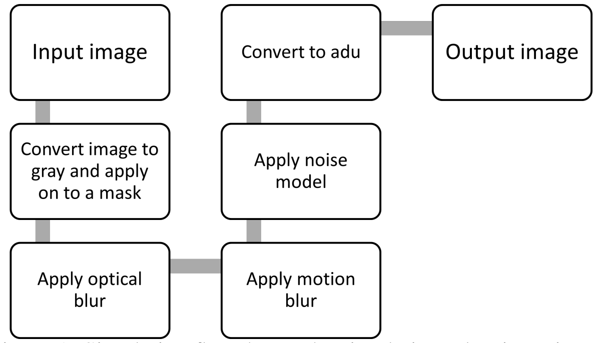

Figure 1: Simulation flowchart. The simulation takes in an image as input and a set of parameters including camera configurations, ambient lux level, degree of motion, and exposure time. The image is then converted to grayscale and optical blurring is applied. The motion blur is then applied to the image. Then the noise model is applied to the image. The image is then converted to analog digital units using the camera configuration values.

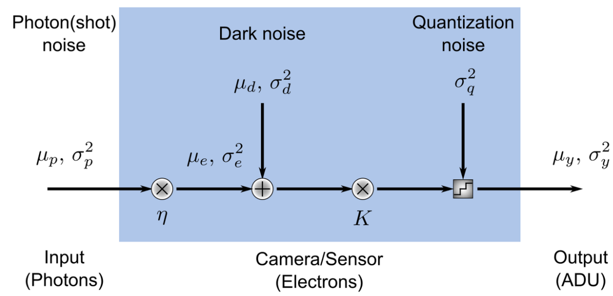

Figure 2: Simulation noise model. In these expressions, μ and σ^2 represent the mean and variance of the number of photons hitting the camera (p), the dark noise (d), and the output signal in ADU's (y). The number of electrons e generated by p photons hitting the active area of the sensor is obtained from the expression for the quantum efficiency η, an engineered property of the camera that in general depends on the wavelength.

A simple disk optical blur model, implemented from Matlab's built-in disk function, is applied to the simulation. When applying the motion blur, a blur kernel is first created using the vector combination of the horizontal pixel movement and the vertical pixel movements, which gives the length of the motion. The blur kernel is then rotated by a transformation matrix which is generated by the angle between the two vectors, this will give the direction of the motion blur. The blur kernel is then normalized and applied to the image in the form of a filter. The noise model for the simulation, as shown in Figure 2, is then applied to the image. The noise model implemented is an extension of that described in Douglas et al. [17]. The image is then converted to analog digital units (ADUs) to simulate the quantization error of the camera, producing the final output image. The simulation is performed on gray-scale images. Example images taken at different lux levels are shown in Figure 3.

The array of simulated images of different degrees of exposure time, lux level, and motion blur are then inputted into Imatest [18] for the calculation of image quality metrics.

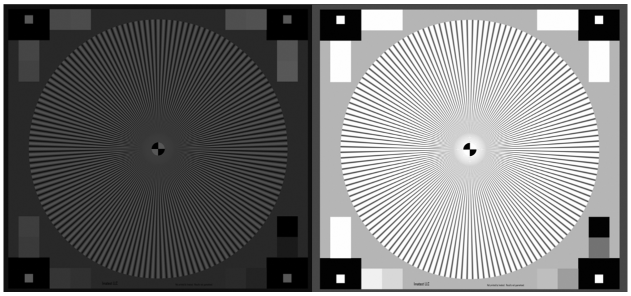

Figure 3: Samples images without motion blur, with light levels of 50 lux on left and 300 lux on the right. Both images were captured under 30ms exposure time.

Results

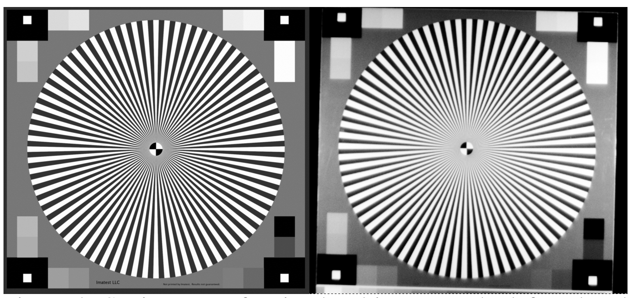

Figure 4: Static scene of a simulated image on the left and real image on the right. Both were captured under 200lux and at 30ms exposure time.

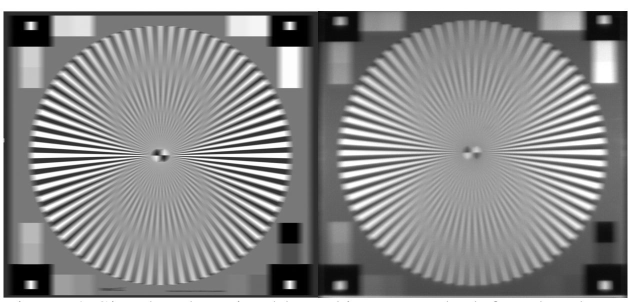

Figure 5: Simulated motion blurred image on the left and real motion blurred image on the right. Both images are approximately at 1500 DX(horizontal pixel movement per second). Both were captured under 200 lux and 30ms exposure time.

The images produced by simulation show a large degree of correlation with real-world images, for both static and motion-blurred images. This can be seen in the examples shown in Figure 4 and Figure 5. Similar blurring at the center of the chart and similar figure eight blur artifacts appear when applying horizontal blurring.

Figure 6 and Figure 7 show the variation of quality metrics as a function of exposure time (10 ms to 30 ms) and degree of horizontal and diagonal pixel movement. We can see from Figure 6 and Figure 7 that, during static scenes, increasing the exposure time will directly improve the image quality metrics which suggests that the information in the image has increased. However, with the higher exposure time, the degree at which motion blur affects image quality also increases. The image quality metrics become less useful as more motion blur is added, resulting in erratic and noisy behavior in the graph for high pixel movement values. The longer the exposure time, the earlier the inconsistent behavior begins to occur. The loss of reliability in the metrics is more apparent in diagonally blurred images in Figure 7 because there is blurring in both the vertical axis and horizontal axis. While somewhat subjective, we can see that the useful range of the graphs the metrics for our camera setting at 30ms exposure and 200 lux illumination, is approximately 900-pixel movement per second, which can be converted to meters per second if the distance and size of the target are known.

Conclusion

This paper has described a simulation that measures a number of image quality metrics as a function of motion blur and camera exposure times, for night-time imaging applications. Increasing the exposure time will increase the amount of information in the image (as measured by SIC) but will also increase the rate at which motion blur affects the image. As well as traditional metrics like MTF50 and SNR, we also examine alternative metrics like SIC and NEQ. Our simulation correlates well with real world images. The results indicating the variation in image quality as a function of motion blur and exposure time may be used in system design as a guide to choosing system parameters to achieve certain performance goals.

Future Works

We plan to extend the research to natural scenes and examine the correlation between the simulation and real-world images. We also plan to improve our simulation to include applications such as rolling shutter cameras and improve our blurring simulation to include localized blurring. We also plan to incorporate other metrics and other image quality targets into our future studies, for example, SNRI [8] and BxU [19]. Other image quality targets such as the slanted edge will be considered for the testing of more extreme scenarios and exposures, as it is much more robust than the Siemens Star chart, albeit less sensitive. We also plan to investigate the relationship between motion blur, image quality metrics, and object detection performance.

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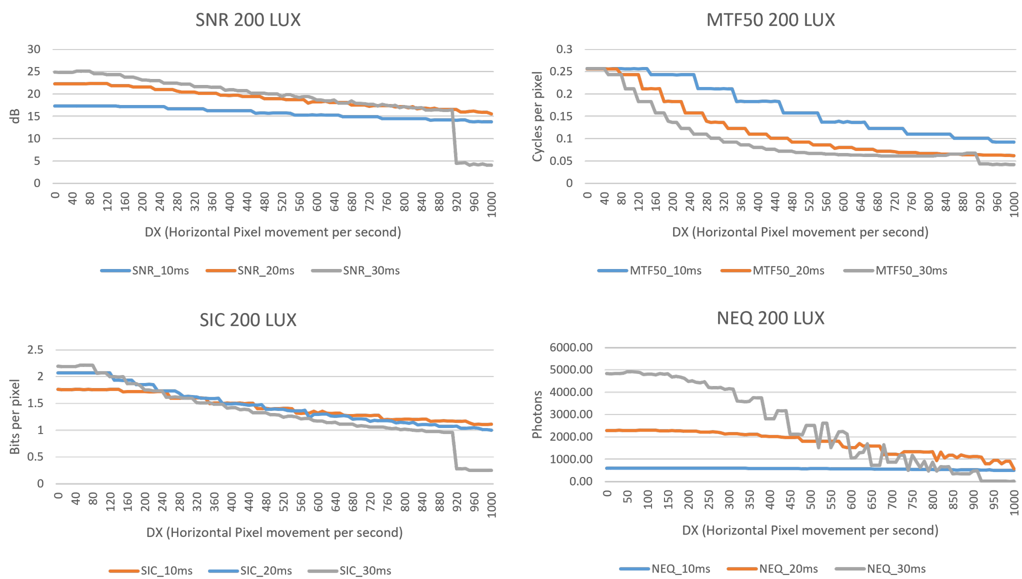

Figure 6: Graph of IQ metrics plotted against horizontal pixel movement per second, with different exposures and constant 200 lux light level

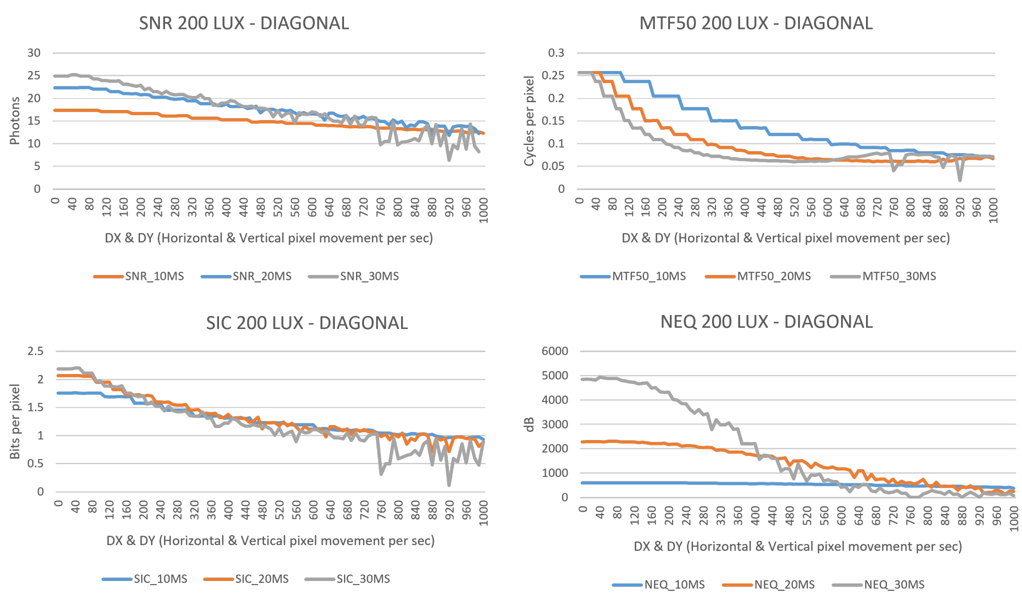

Figure 7: Graph of IQ metrics plotted against diagonal pixel movement per second, with different exposures and constant 200 lux light level The diagonal pixel movement is a combination of horizontal and vertical pixel movement.

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Author Biography

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Enda Ward *received his B.E. in Electronic Engineering in 1999 from the University of Galway and his MEng.SC master's degree in research in Electronic Engineering in 2002, with a focus on Biomedical Electronics. He is responsible for defining the camera product roadmap for surround and automated driving applications within Valeo. He holds several patents in the area of automotive vision.*

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