The Effect of Motion Blur and Signal Noise on Image Quality in Low Light Imaging

Eero Kurimo[1], Leena Lepistö[2], Jarno Nikkanen[2], Juuso Grén[2], Iivari Kunttu[2], and Jorma Laaksonen[1]

[1] Helsinki University of Technology
Department of Information and Computer Science
P.O. Box 5400, FI-02015 TKK, Finland
jorma.laaksonen@tkk.fi
http://www.tkk.fi
[2] Nokia Corporation
Visiokatu 3, FI-33720 Tampere, Finland
{leena.i.lepisto,jarno.nikkanen,juuso.gren,
iivari.kunttu}@nokia.com
http://www.nokia.com

Abstract. Motion blur and signal noise are probably the two most dominant sources of image quality degradation in digital imaging. In low light conditions, the image quality is always a tradeoff between motion blur and noise. Long exposure time is required in low illumination level in order to obtain adequate signal to noise ratio. On the other hand, risk of motion blur due to tremble of hands or subject motion increases as exposure time becomes longer. Loss of image brightness caused by shorter exposure time and consequent underexposure can be compensated with analogue or digital gains. However, at the same time also noise will be amplified. In relation to digital photography the interesting question is: What is the tradeoff between motion blur and noise that is preferred by human observers? In this paper we explore this problem. A motion blur metric is created and analyzed. Similarly, necessary measurement methods for image noise are presented. Based on a relatively large testing material, we show experimental results on the motion blur and noise behavior in different illumination conditions and their effect on the perceived image quality.

1 Introduction

The development in the area of digital imaging has been rapid during recent years. The camera sensors have become smaller whereas the number of pixels has increased. Consequently the pixel sizes are nowadays much smaller than before. This is particularly the case in the digital pocket cameras and mobile phone cameras. Due to the smaller size, one pixel is able to receive smaller number of photons within the same exposure time. On the other hand, the random noise caused by various sources is present in the obtained signal. The most effective way to reduce the relative amount of noise in the image (i.e. signal to noise ratio, SNR) is to use longer exposure times, which allows more photons to be observed by the sensor. However, in the case of long exposure times, the risk of motion blur increases.

A.-B. Salberg, J.Y. Hardeberg, and R. Jenssen (Eds.): SCIA 2009, LNCS 5575, pp. 81–90, 2009.

Motion blur occurs when the camera or the subject moves during the exposure period. When this happens, the image of the subject moves to different area of the camera sensor photosensitive surface during the exposure time. Small camera movements soften the image and diminish the details whereas larger movements can make the whole image incomprehensible [8]. This way, either the camera movement or the movement of the object in the scene are likely to become visible in the image, when the exposure time is long. This obviously is dependent on the manner how the images are taken, but usually this problem is recognized in low light conditions in which long exposure times are required to collect enough photons to the sensor pixels. The decision on the exposure time is typically made by using an automatic exposure algorithm. An example of this kind algorithm can be found in e.g. [11]. A more sophisticated exposure control algorithm presented in [12] tries to optimize the ratio between signal noise and motion blur.

The perceived image quality is always subjective. Some people prefer somewhat noisy but detailed images over smooth but blurry images, and some tolerate more blur than noise. The image subject and the purpose of the image also affect on the perceived image quality. For example, images containing text may be a bit noisy but still readable, similarly e.g. images of landscapes can sometimes be a bit blurry. In this paper, we analyze the effect of motion blur and noise on the perceived image quality and try to find the relationship of these two with respect to the camera parameters such as exposure time. The analysis is based on the measured motion blur and noise and the image quality perceived by human observers.

Although both image noise and motion blur have been intensively investigated in the past, their relationship and their relative effect on the image quality has not been studied in the same extent. Especially the effect of the motion blur on the image quality has not received much attention. In [16], a model to estimate the tremble of hands was presented and it was measured, but it was not compared to noise levels in the image. Also the subjective image quality was not studied. In this paper, we analyze the effects of the motion blur and noise to the perceived image quality in order to optimize the exposure time in different levels of image quality, motion blur, noise and illumination. For this purpose, a motion blur metric is created and analyzed. Similarly, necessary measurement methods for image noise are presented. In a quite comprehensive testing part, we created a set of test images captured by several test persons. The relationship between the motion blur and noise is measured by means of these test images. The subjective image quality of the test set images is evaluated and the results are compared to the measured motion blur and noise in different imaging circumstances.

The organization of this paper is the following: Sections 2 and 3 present the framework for the motion blur and noise measurements, respectively. In section 4, we present the experiments made to validate the framework presented in this paper. The results are discussed and conclusions drawn in section 5.

2 Motion Blur Measurements

Motion blur is one of the most significant reasons for image quality decrease. Noise is also influential, but it increases gradually and can be accurately estimated from the signal values. Motion blur, on the other hand, has no such benefits. It is very difficult to estimate the amount of motion blur either a priori or a posteriori. It is even more difficult to estimate the motion blur a priori from the exposure time because motion blur only follows a random distribution based on the exposure time and the characteristics of the camera and the photographer. The expected amount of motion blur can be estimated a priori if the knowledge on the photographer behavior is available, but because of the high variance of the motion blur distribution of the exposure time, the estimation is very imprecise at best.

The framework for motion blur inspection has been presented in [8], in which types of motion blur are presented. In [8], a three-dimensional model, in which the camera may move along or spin around three different axes, was presented. Motion blur is typically modeled as angular blur, which is not necessarily always the case. It has been shown that camera motion should be considered as straight linear motion when the exposure time is less than 0.125 seconds [16]. If the point spread function (PSF) is known, or it is possible to estimate, then it is possible to correct the blur by using Wiener filtration [15]. The amount of blur can be estimated in many manners. A basic approach is to detect the blur in the image by using an edge detector, such as Canny method, or the local scale control method proposed by James and Steven [6], and measure the edge width at each edge point [10]. Another more practical method was proposed in [14], which uses the characteristics of sharp and dull edges after Haar wavelet transform. It is clear that the motion blur analysis is more reliable in the cases where two or more consequent frames are available [13]. In [9], the strength and direction of the motion was estimated this way, and this information was used to reduce the motion blur. Also in [2], a method for estimating and removing blur from two blurry images was presented. A two camera approach was presented also in [1]. The methods based on several frames, however, are not always practical in all mobile devices due to their memory requirements.

2.1 Blur Metric

An efficient and simple way of measuring the blur from the image is to use laser spots projected to the image subject. The motion blur can be estimated from the size of the laser spot area [8]. To get a more reliable motion blur measurement result and also include the camera rotation around the optical axes (roll) into measurement, the use of multiple laser spots is preferable. In the experiments related to this paper, we have used three laser spots located in center, and two corners of the scene. To make the identification process faster and easier, a smaller image is cropped from the image, and the blur pattern is extracted by means of adaptive thresholding, in which the laser spot threshold could be determined by keeping the ratio between the threshold and the exposure time at a constant level. This method produced roughly the same size laser spot regions of no motion blur with varying exposure times.

Once the laser spot regions in each image are located, the amount of motion blur in the images can be estimated. First, a skeleton is created by thinning the thresholded binary laser spot region image. The thinning algorithm, proposed as Algorithm A1 in [4] and implemented in the Image processing toolbox of the Matlab software, is iterated until the final homotopic skeleton is reached. After the skeletonization, the centroid, orientation and major and minor axis lengths of the best-fit ellipse fit to the skeleton pixels can be calculated. The major axis length is then used as a scalar measure for the blur of the laser spot.

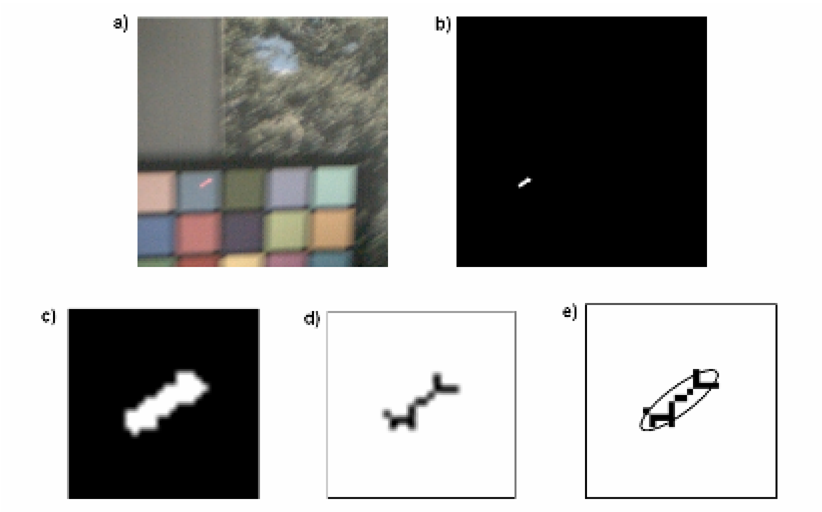

Fig. 1. a) Blur measurement process: a) piece extracted from the original image, b) the thresholded binary image c) enlarged laser spot, d) its extracted homotropic skeleton and e) the ellipse fitted around the skeleton

Figure 1 illustrates the blur measurement process. First, subfigures 1a and 1b show a piece extracted from the original image and the corresponding thresholded binary image of the laser spot. Then, subfigures 1c, 1d and 1e display the enlarged laser spot, its extracted homotopic skeleton and finally the best-fit ellipse, respectively. In the case of this illustration, the blur was measured to be 15.7 pixels in length.

3 Noise Measurement

During the decades, digital camera noise research has identified many additive and multiplicative noise sources, especially inside the image sensor transistors. Some noise sources have even been completely eliminated. Dark current is the noise generated by the photosensor voltage leaks independent of the received photons. The amount of dark current noise depends on the temperature of the sensors, the exposure time and the physical properties of the sensors. Shot noise comes from the random arrival of photons to a sensor pixel. It is the dominant noise source at the lower signal values just above the dark current noise. The arrivals of photons to the sensor pixel are uncorrelated events. This means that the number of captured photons by a sensor pixel during a time interval can be described as a Poisson process. It follows that the SNR of a signal that follows the Poisson distribution has the SNR that is proportional to the number of photons captured by the sensor. Consequently, the effects of shot noise can be reduced only by increasing the number of captured photons. Fixed pattern noise (FPN) comes from the nonuniformity of the image sensor pixels. It is caused by imperfections and other variations between the pixels, which result in slightly different pixel sensitivities. The FPN is the dominant noise source with high signal values. It is to be noticed that the SNR of fixed pattern noise is independent of signal level and remains at a constant level. This means that the SNR cannot be affected by increasing the light or exposure time, but only by using a more uniform pixel sensor array.

The total noise of the camera system is a quadrature sum of its dark current, shot and fixed pattern noise components. These can be studied by using the photon transfer curve (PTC) method [7]. Signal and noise levels are measured from sample images of a uniformly illuminated uniform white subject in different exposure times. The measured noise is plotted against the measured signal on a log-log scale. The plotted curve will have three distinguishable sections as illustrated in figure 2a.

With the lowest signals the signal noise is constant, which indicates the read noise consisting of the noise sources independent of the signal level, such as the dark current and on-chip noise. As the signal value increases, the shot noise becomes the dominant noise source. Finally the fixed pattern noise becomes the dominant noise source, and indicating the full well of the image sensor.

3.1 Noise Metric

For a human observer, it is possible to intuitively approximate how much visual noise there is present in the image. However, measuring this algorithmically has proven to be a difficult task. Measuring noise directly from the image without any a priori knowledge on the camera noise behavior is a challenging task but has not received much attention. Foi et al [3] have proposed an approach, in which the image is segmented into regions of different signal values $y \pm \delta$ where y is the signal value of the segment and δ is a small variability allowed inside the segment.

Signal noise is in practice generally considered as the standard deviation of subsequent measurements of some constant signal. An accurate image noise measurement method would be to measure the standard deviation of a group of pixels inside an area of uniform luminosity. An old and widely used camera performance analysis method is based on the photon transfer curve (PTC) [7]. Methods similar to the one used in this study have been applied in [5]. The PTC method generates a curve showing the standard deviation of an image sensor pixel value in different signal levels. The noise σ should grow monotonically with the signal S according to:

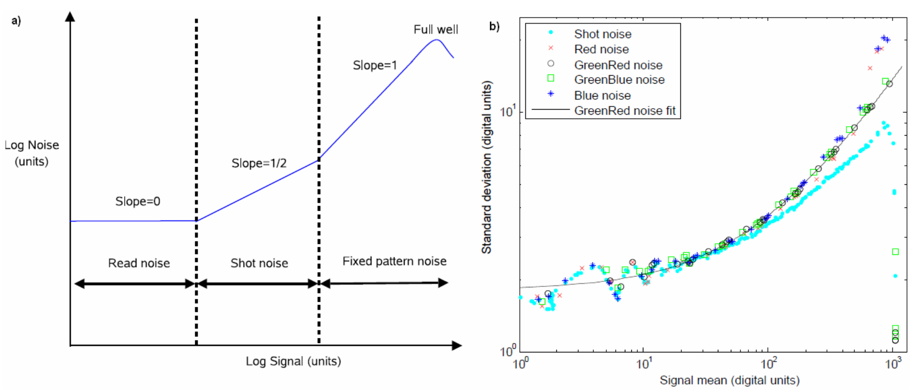

Fig. 2. a) Total noise PTC illustrating three noise regimes over the dynamic range. b) Measured PTC featuring total noise with different colors and the shot noise [8].

$$\sigma = aS^b + c \tag{1}$$

before reaching the full well. If the noise monotonicity hypothesis holds for the camera, the noisiness of each image pixel could be directly estimated from the curve when knowing the signal value.

In our calibration procedure, the read noise floor was first determined using dark frames by capturing images without any exposure to light. Dark frames were taken with varying exposure times to determine also the effect of longer exposure times. Figure 2b shows noise measurements made for experimental image data. The noise measurement was carried out in three color channels and shot noise from images when fixed pattern noise is removed. The noise model was created by fitting the equation (1) to the green pixel values using values a = 0.04799, b = 0.798 and c = 1.819.

For the signal noise measurement, a uniform white surface was located into the scene, and the noise level of the test images was estimated as a local standard deviation on this surface. Similarly, the signal value estimate was the local average of the signal on this region. The signal to noise ratio (SNR) can be calculated as a ratio between these two.

4 Experiments

The goal of the experiments was to obtain sample images with good spectrum of different motion blurs and noise levels. The noise, motion blur and the image had to be able to be measured from the sample images. All the experiments were carried out in an imaging studio in which the illumination levels can be accurately controlled.

All the experiments were made by using a standard mobile camera device containing a CMOS sensor with 1151x864 pixel resolution. There were totally four test persons with varying amount of experience on photography. Each person captured hand held camera photographs in four different illumination levels and with four different exposure times. At each setting, three images were taken, which means that each test person took totally 48 images. The illumination levels were 1000, 500, 250, and 100 lux, and the exposure time varied between 3 and 230 milliseconds according to a specific exposure time table defined for each illumination level so that the used exposure times followed a geometric series 1, 1/2, 1/4, 1/8 specified for each illumination level. The exposure time 1 at each illumination level was determined so that the white square in color chart had the value corresponding 80 % of the saturation level of the sensor. in this manner, the exposure times were obviously much lower in 1000 lux (ranging from 22ms to 3ms) than in 100 lux (ranging from 230ms to 29ms). The scene setting can be seen in figure 3, which also shows the three positions of the laser spots as well as white region for the noise measurement. Once the images were taken, the noise level was measured from each image by using the method presented in section 3.2 at the region of white surface. In addition, motion blur was measured based on the three laser spots with a method presented in section 2.1. The average value of the blur measured in three laser spot regions was used to represent the motion blur in the corresponding image.

Fig. 3. Two example images from the testing in 100 lux illumination. The exposure times in left and right are 230 and 29 ms, respectively. This causes motion blur in left and noise in right side image. The subjective brightness of the images is adjusted to the same level by using appropriate gain factors. The three laser spots are clearly visible in both images.

After that, the subjective visual image quality evaluation was carried out. For the evaluation, the images were processed by using adjusted gain factors so that the brightness of all the images was at the same level. There were totally 5 persons who independently evaluated the image quality. This was made in terms of overall quality, blur and noise. The evaluating persons gave a grade in scale between zero and five for each image, zero meaning poor and five meaning excellent image quality with no apparent quality degradations. The image quality was evaluated in three manners, in terms of overall quality, motion blur as well as noise. The evaluating persons gave the grades for each image in these three manners.

4.1 Noise and Motion Blur Analysis

To evaluate the perceived image quality against the noise and motion blur metrics presented in this paper, we compared them to the subjective evaluation results. This was made by taking the average subjective image quality evaluation results for each sample image, and plotting them against the measurements calculated to these images. The result of this comparison is shown in figure 4. As presented in this figure, both noise and motion blur metrics follow well the subjective interpretation of these two image characteristics. In the case of SNR, the perceived image quality smoothly rises with increasing SNR in the cases where there is no motion blur. On the other hand, it is essential to note that if there is significant motion in the image, the image quality grade is poor even if the noise level is relatively low. When considering the motion blur, however, an image is considered a relatively good quality even though there was some noise in it. This supports a conclusion that human observers find motion blur more disturbing than noise.

4.2 Exposure Time and Illumination Analysis

The second part of the analysis considered the relationship of exposure time and motion blur versus the perceived image quality. This analysis is essential in terms of the scope of this paper, since the risk of tremble of hands increases with increasing

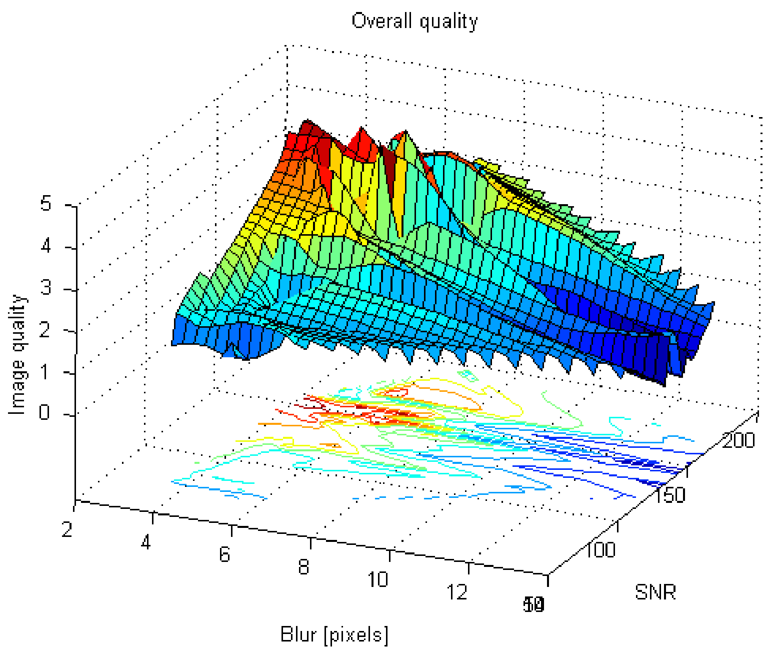

Fig. 4. Average overall evaluation results for the image set plotted versus measured blur and SNR

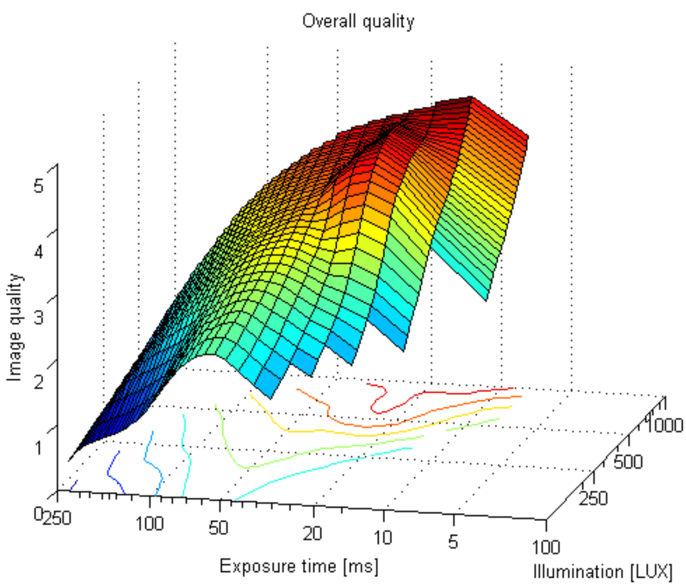

Fig. 5. Average overall evaluation results for the image set plotted versus illumination and exposure time

exposure time. Therefore, the analysis of optimal exposure times is a key factor in this study. Figure 5 shows the average grades given by the evaluating persons as a function of exposure time and illumination. The plot presented in figure 5 shows that image quality is clearly the best with high illumination levels, but it slowly decreases when illumination or exposure time decreases. This is an obvious result in general. However, the value of this kind of analysis is the fact that it can be used to optimize the exposure time at different illumination levels.

5 Discussion and Conclusions

Automatically determining the optimal exposure time using a priori knowledge is an important step in many digital imaging applications, but has not much been publicly studied. Because signal noise and motion blur are the most severe reasons for digital image quality degradations, and both are heavily affected by the exposure time, their effects on the image quality were the focus of this paper. Motion blur distribution and camera noise in different exposure times should be automatically estimated from the sample images taken just before the actual shot using recent advances in image processing. Using these estimates, the expected image quality for different exposure times can be determined using the methods of the framework presented in this paper.

In this paper, we have presented a framework for the analysis of the relationship between noise and motion blur. In addition, the information given by the tools provided in this paper is able to steer the optimization of the exposure time in different lighting conditions. It is obvious that a proper method for the estimation of the camera motion is needed to make this kind of optimization more accurate, but even a rough understanding of the risk of the motion blur on each lighting level greatly helps e.g. the development of more accurate exposure algorithms.

To make the model of the motion blur and noise relationship more accurate, an extensive testing with a covering test person group of different types of people is needed. However, the contribution of this paper is clear: a simple and robust method for the motion blur measurement and related metrics are developed, and the ratio between measured motion blur and measured noise could be determined in different lighting conditions. The effect of this on the perceived image quality was evaluated. Hence the work presented in this paper is a framework that can be used in the development of methods for the optimization of the ratio between noise and motion blur.

One aspect that is not considered in this paper is the impact of noise reduction algorithms. It is obvious that by utilizing a very effective noise reduction algorithm it is possible to use shorter exposure times and higher digital or analogue gains. This is because the resulting amplified noise can be reduced in the final image, hence improving the perceived image quality. An interesting topic for further study would be to quantify the difference between simple and more advanced noise reduction methods in this respect.

References

1. Ben-Ezra, M., Nayat, S.K.: Motion based motion deblurring. IEEE Transactions on Pattern Analysis and Machine Intelligence 26(6), 689–698 (2004)
2. Cho, S., Matsushita, Y., Lee, S.: Removing non-uniform motion blur from images (2007)

3. Foi, A., Alenius, S., Katkovnik, V., Egiazatrian, K.: Noise measurement for raw-data of digital imaging sensors by automatic segmentation of non-uniform targets. IEEE Sensors Journal 7(10), 1456–1461 (2007)
4. Guo, Z., Hall, R.W.: Parallel Thinning with Two-Subiteration Algorithms. Communications of the ACM 32(3), 359–373 (1989)
5. Hytti, H.T.: Characterization of digital image noise properties based on RAW data. In: Proceedings of SPIE, vol. 6059, pp. 86–97 (2006)
6. James, H., Steven, W.: Local scale control for edge detection and blur estimation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 699–716 (1996)
7. Janesick, J.: Scientific Charge Coupled Devices, vol. PM83 (2001)
8. Kurimo, E.: Motion blur and signal noise in low light imaging, Master Thesis, Helsinki University of Technology, Faculty of Electronics, Communications and Automation, Department of Information and Computer Science (2008)
9. Liu, X., Gamal, A.E.: Simultaneous image formation and motion blur restoration via multiple capture,....
10. Marziliano, P., Dufaux, F., Winkler, S., Ebrahimi, T., Genimedia, S.A., Lausanne, S.: A no-reference perceptual blur metric. In: Proceedings of International Conference on Image Processing, vol. 3 (2002)
11. Nikkanen, J., Kalevo, O.: Menetelmä ja järjestelmä digitaalisessa kuvannuksessa valotuksen säätämiseksi ja vastaava laite. Patent FI 116246 B (2003)
12. Nikkanen, J., Kalevo, O.: Exposure of digital imaging. Patent application PCT/FI2004/050198 (2004)
13. Rav-Acha, A., Peleg, S.: Two motion blurred images are better than one. Pattern Recognition letters 26, 311–317 (2005)
14. Tong, H., Li, M., Zhang, H., Zhang, C.: Blur detection for digital images using wavelet transform. In: Proceedings of IEEE International Conference on Multimedia and Expo., vol. 1 (2004)
15. Wiener, N.: Extrapolation, interpolation, and smoothing of stationary time series (1992)
16. Xiao, F., Silverstein, A., Farrell, J.: Camera-motion and effective spatial resolution. In: International Congress of Imaging Science, Rochester, NY (2006)