Over exposed image information recovery via stochastic resonance*

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Over exposure is rather annoying in photo taking. However, in some severe light conditions over exposure is inevitable using conventional cameras due to the limitation of dynamic range of the image sensor. The over exposed information would be completely lost and unrecoverable. In order to cope with this problem, we propose a novel technique in which the noise is used to enlarge the dynamic range of the image sensor. The essential mechanism that noise contributes to the information recovery is investigated. It is also proved that the visibility of regained information can reach the peak when specifically added noise is synchronized with the image sensor, thus activating the phenomenon of stochastic resonance (SR). Four different types of noises are investigated to show the effects of variant distributions on the quality of recovered information. The experimental outcomes are consistent with our theoretical results, which indicates that the SR-based lost information recovery is quite promising.

Keywords: stochastic resonance, image information recovery, dynamic range, over exposure

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1. Introduction

Stochastic resonance (SR) is a phenomenon that disordered noises concentrate together under certain conditions to draw huge and well-organized power. This concept was first put forward by Benzi *et al.*[1,2] in 1981 to address the periodicity of ice ages. In order to describe the mechanism of SR, we consider a heavily damped particle moving in an asymmetric double-well potential that is driven by weak periodic force (Fig. 1). Generally, the weak force itself is unable to trigger the particle to shift between the two potential wells. However, if the double-well potential is interfered by noise to a certain intensity which could synchronize with the periodic force, the particle would transit between two wells in accordance with the periodic force. This synchronization is called stochastic resonance.[3] There are three basic ingredients required for the occurrence of SR: (i) an energetic activation barrier; (ii) a weak coherent input; (iii) a source of noise. A nonlinear barrier is the fundamental environment; weak input is the submerged power; and noise is the vital lead to stochastic resonance.

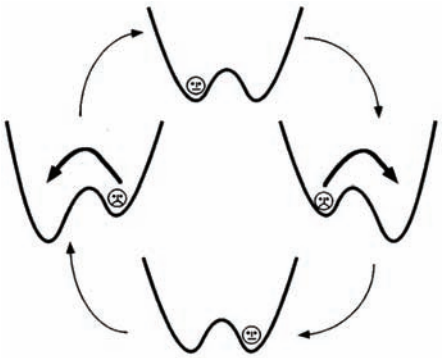


Fig. 1. The mechanism of stochastic resonance.

Since the concept of SR was raised and the effect was experimentally verified, the idea of utilizing noise to enhance the performance of a nonlinear system has been widely investigated and applied to various scientific fields such as physics, chemistry, biomedical sciences, and financial market systems[3–6] over the last few decades. For example, the balance control abilities of elders can be improved with the help of noise.[4] A profoundly deaf person can better get to know speech if a certain amount of noise is added to the vowel coding for cochlear implants.[5] There are other applications of SR to the field of signal processing[7,8] and target detection.[9]

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Image processing is an extremely hot research area in modern science.[10−13] Some work has already been done to reduce noise level and enhance the signal-to-noise ratio (SNR) of images using parameter-induced stochastic resonance.[14,15] Our work aims at recovering over exposed information of an image by adding specified noise to activate the SR effect of the system. It is proved in this paper that the lost information can be clearly regained when noise induced stochastic resonance occurs. Such information could be essential in a decision making process such as pattern recognition[16] and is hardly recoverable for any post-processing method.

The rest of the present paper is organized as follows. In Section 2, we introduce the framework, classification, and current development of the digital image sensor, along with the limitations of the conventional image sensor compared with human eyes. In Section 3, the theoretical basis of our proposed SR technique is delivered. Two examples of lost information recovery including locally over exposed portrait and over exposed plate number information recovery using the technique discussed in Section 3 are shown in Section 4. The conclusions and our future investigations are drawn in Section 5.

2. An introduction to the image sensor and its limitations

An image sensor (Fig. 2) is a device which is able to convert an optical image into electric information. It is widely used in digital cameras, digital videos, and other imaging devices. There are typically two types of image sensors: the charge-coupled device (CCD) and the complementary metal–oxide–semiconductor (CMOS).[17] Both types fulfill the identical task of capturing light and converting it into electric information. The CCD is an analog device. When light is captured by the chip it is held as a small electrical charge in each pixel sensor. These charges are converted into voltage one pixel at a time while they are picked up from the chip. A dedicated circuitry in the camera converts the voltage into digital information. The CMOS is composed mainly of silicon and germanium. Semiconductors with positive and negative charges are attached on the CMOS. The generated current via these complementary charges is converted into electric information which is finally used for imaging.

The ultimate goal of a camera is to record the scene of human sight onto its image sensor. Unfortunately due to technical obstacles it is impossible for any image sensor to rebuild an image identical to what we have seen with our eyes. One of the challenges we have confronted is the dynamic range. Dynamic range is the ratio between the brightest and the darkest luminance that can be identified by a sensor in a single scene.[18] The dynamic range of a modern image sensor is around 2^8:1 to 2^{12}:1, while the mean dynamic range of a human eye is around 10000:1 and in some extreme circumstances can reach as high as 1000000:1.[19] In photographing, dynamic range can also be defined as the luminance range of a scene being captured.[20] If the dynamic range of an image sensor is $[L_{\min}, L_{\max}]$, the luminance of a scene larger than $L_{\max}$ and smaller than $L_{\min}$ is recorded as totally blank (which is called over exposure in the former case and under exposure in the latter one). There exists no information in such cases. Generally, image sensors are more sensitive to highlight. A certain level of under exposure can still be recovered by post processing while nothing can be done when the same level of over exposure occurs.



Fig. 2. Image sensor.

3. How to use noise induced stochastic resonance to recover lost information

Imagine that a view captured by human eyes is recorded as $I(x, y)$. When taken down by camera it becomes

$$S(x,y) = g\left[I(x,y)\right] = \begin{cases} L_{\min}, & I(x,y) < L_{\min}, \\ I(x,y), & L_{\min} < I(x,y) < L_{\max}, \\ L_{\max}, & I(x,y) > L_{\max}. \end{cases} \quad (1)$$

The image sensor can be viewed as a saturation system that is linear when the luminance is within the dynamic range and constant once exceeded.[21]

If we add specified noise to the image sensor in advance and let it be taken down along with the image

$I(x,y)$, we will obtain the following data:

$$S_n(x,y) = g\left[I(x,y) + n(x,y)\right], \tag{2}$$

where $n(x,y)$ is specified noise with probability density function (PDF) $p(n)$. According to Eq. (1) and Eq. (2), the expectation of $S_n(x,y)$ can be calculated as

$$\begin{aligned} E\left[S_n(x,y)\right] = {} & L_{\min}\int_{-\infty}^{L_{\min}} p(\xi - I(x,y))\mathrm{d}\xi \\ & + \int_{L_{\min}}^{L_{\max}} \xi p(\xi - I(x,y))\mathrm{d}\xi \\ & + L_{\max}\int_{L_{\max}}^{+\infty} p(\xi - I(x,y))\mathrm{d}\xi. \end{aligned} \tag{3}$$

In order to investigate the effect of noise, we examine four types of distributions of $n(x,y)$,[22] which are

i) Gaussian distribution

$$p_1(n) = \frac{1}{\sqrt{2\pi}\sigma}\cdot\exp\left[-\frac{(n-m)^2}{2\sigma^2}\right]; \tag{4}$$

ii) Uniform distribution

$$p_2(n) = \begin{cases} \dfrac{1}{2\sqrt{3}\sigma}, & m-\sqrt{3}\sigma \le n \le m+\sqrt{3}\sigma, \\ 0, & \text{otherwise}; \end{cases} \tag{5}$$

iii) Rayleigh distribution

$$p_3(n) = \begin{cases} \dfrac{4-\pi}{2\sigma^2}\left(n-m+\sigma\sqrt{\dfrac{\pi}{4-\pi}}\right)\exp\left[-\dfrac{(4-\pi)\left(n-m+\sigma\sqrt{\dfrac{\pi}{4-\pi}}\right)^2}{4\sigma^2}\right], & n \ge m-\sigma\sqrt{\dfrac{\pi}{4-\pi}}, \\ 0, & \text{otherwise}; \end{cases} \tag{6}$$

iv) Chi-square distribution:

$$p_4(n) = \begin{cases} \dfrac{\left(n+\dfrac{\sigma^2}{2}-m\right)^{(\sigma^2-4)/4}\exp\left(-\dfrac{2n+\sigma^2-2m}{4}\right)}{2^{\sigma^2/4}\Gamma\left(\dfrac{\sigma^2}{4}\right)}, & n \ge m-\dfrac{\sigma^2}{2}, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where m and σ^2 are the expectation and the variance of noise. Figure 3 shows $E\left[S_n(x,y)\right]$ values each as a function of original luminance $I(x,y)$, where $L_{\min}=0$ and $L_{\max}=1$. We find that $S_n(x,y)$ is within the range of $[L_{\min}, L_{\max}]$ when $I(x,y)$ shifts from -1 to 2, which is distinguishable only within the range of $[0,1]$ if no noise is added. Therefore we conclude that the dynamic range of the image sensor can be widened by noise.

Since we have realized the benefit of noise, another question is raised: which type and what level of noise are best for recovering lost information in images? Assume two over exposed luminances I_1 and I_2 ($I_1, I_2 > L_{\max}$). We substitute them into Eq. (3) and define as the visibility of I_1 and I_2 when the over exposed information is retrieved. Since the PDF $p(n)$ is related to noise expectation m and variance σ^2 according to Eqs. (4)–(7), and for convenience we often set m to be zero, thus the visibility is a function of I_1, I_2, type and variance of specified noise

$$\begin{aligned} V(I_1,I_2) = {} & \frac{E\left[S_{n1}(x,y)\right]}{E\left[S_{n2}(x,y)\right]} \\ = {} & \frac{L_{\min}\int_{-\infty}^{L_{\min}} p(\xi-I_1)\mathrm{d}\xi + \int_{L_{\min}}^{L_{\max}} \xi p(\xi-I_1)\mathrm{d}\xi + L_{\max}\int_{L_{\max}}^{+\infty} p(\xi-I_1)\mathrm{d}\xi}{L_{\min}\int_{-\infty}^{L_{\min}} p(\varsigma-I_2)\mathrm{d}\varsigma + \int_{L_{\min}}^{L_{\max}} \varsigma p(\varsigma-I_2)\mathrm{d}\varsigma + L_{\max}\int_{L_{\max}}^{+\infty} p(\varsigma-I_2)\mathrm{d}\varsigma}. \end{aligned} \tag{8}$$

Figure 4 shows theoretical and simulated visibilities of the two over exposed luminances ($I_1=1$, $I_2=1.5$ while $L_{\max}=1$) each as a function of noise variance σ^2 under four different types of PDFs. We find a common feature of the four curves: as the noise variance grows larger, the visibility will first be improved and reach a peak before descending. $V_{\max}$ is achieved when specifically added noise is synchronized with the saturation system of the image sensor. We call this phenomenon the stochastic resonance (SR), and the corresponding system the SR system.

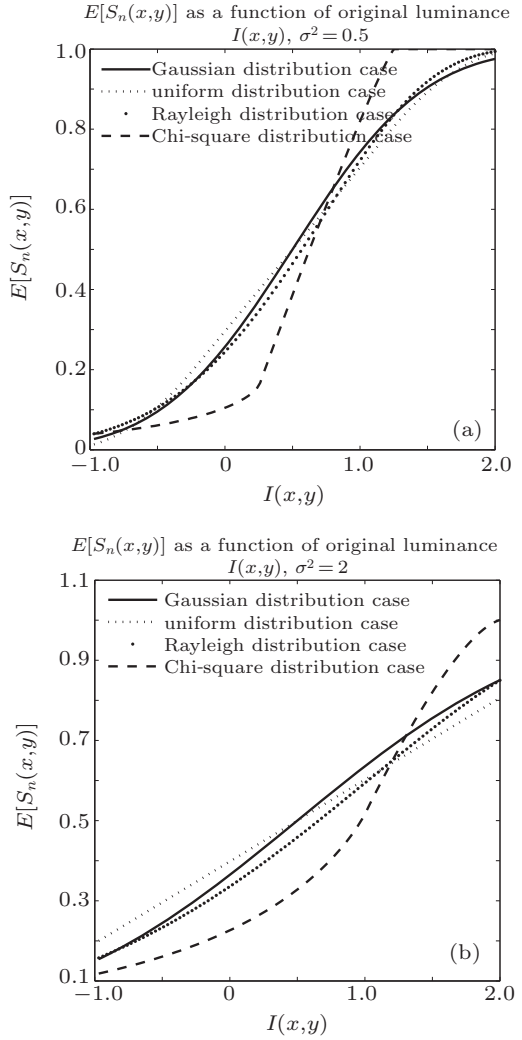


Fig. 3. $E\,[S_n(x,y)]$ values each as a function of original luminance $I(x,y)$, where $L_{\min} = 0$, $L_{\max} = 1$, the noise variance is 0.5 for panel (a) and 2 for panel (b).

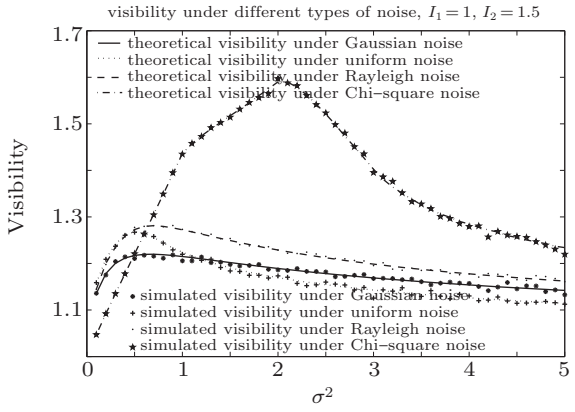


Fig. 4. Theoretical and simulated visibilities each as a function of noise variance σ^2, where $I_1 = 1$, $I_2 = 1.5$, and $L_{\max} = 1$.

By comparison with these four types of noise, we find in the case of Gaussian, uniform, and Rayleigh distribution, the visibility peak is reached when noise variance σ^2 is around 0.5, while in the Chi-square distribution case the peak is reached when σ^2 is around 2. Although the peak visibility of the Chi-square case is much higher, the noise level in the recovered image is also very high. Thus unless in the case where luminance difference is extremely important (such as in objective recognition) or a large number of samples are available for averaging, it is not appropriate to use this type of noise to recover images. Moreover, when $\sigma^2 < 0.5$, the visibility in the Chi-square case is the poorest and that in the uniform case is the best. Combining Fig. 3 it is clear that in the Chi-square case, the over exposed information exceeding 1.2 is unrecoverable when noise variance σ^2 is 0.5. In most cases it is more suitable to use the other three types of noise.

4. Applications to over exposed image recovery

When we take a portrait under severe light conditions such as in the midnoon sunshine, local over exposure is often encountered. Some parts of our face are directly exposed to sun light while others are in the shade. The dynamic range of such a scene would be extremely large and it is impossible to record both highlight and shadow information in one picture. However, if we add specified noise into the image sensor in advance, the portrait taken down will contain more information than the conventional shot, while, of course, at the expense of getting a little bit noisier. Moreover, if the local over exposure is limited to some small areas, we can do the following operation to suppress additional noise:

$$S_n(x,y) = g\,[I(x,y) + n(x,y)] - n(x,y). \qquad (9)$$

Since $n(x,y)$ is specifically added, when subtracted, the previously added noise in most parts of image can be removed. Figure 5 shows the effect of SR based local over exposed image recovery. Figure 5(a) shows a simulation case where a portrait is taken by conventional camera. Due to dynamic range limitation of the image sensor, part of the woman's face and some of the background are over exposed. If we take the same portrait using the model of Eq. (2), the result is shown in Fig. 5(b) from which all the lost details are regained at the expense of more noises generated. When subtracting the noise using the model of Eq. (9) the final recovered image in shown in Fig. 5(c) where a large amount of noise is eradicated.

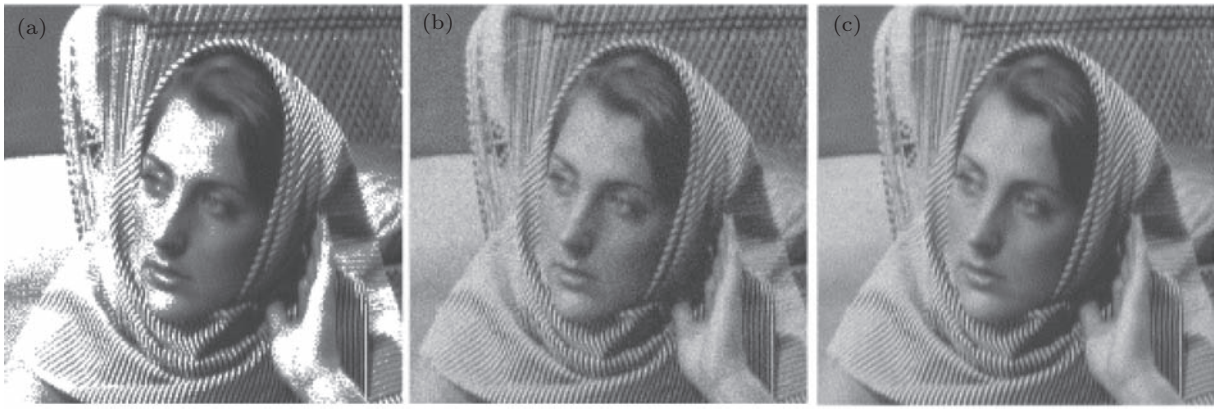


Fig. 5. (a) The local over exposed portrait taken by conventional camera. (b) Recovered results using model of Eq. (2). (c) Recovered results using model of Eq. (9) where a great quantity of noises are removed.

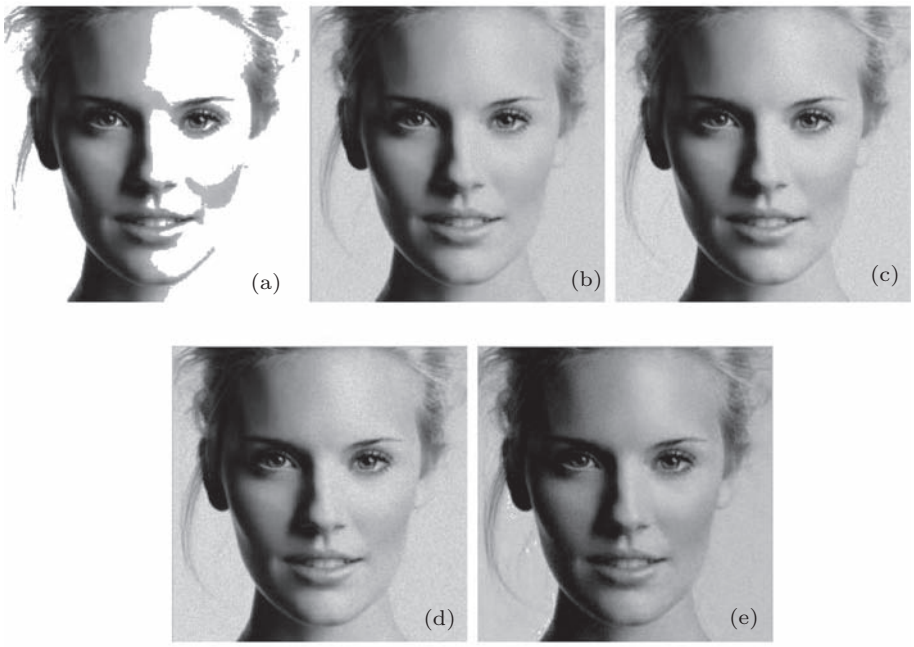


Fig. 6. (a) The original local over exposed portrait. (b), (c), (d), (e) the recovered images by using model of Eq. (9) with Gaussian, uniform, Rayleigh, and Chi-square respectively.

Figure 6 shows an example of an over exposed portrait recovered by different types of specifically added noises. Figure 6(a) shows the original local over exposed portrait. Figures 6(b)–6(e) show the recovered image processed by noise with Gaussian, uniform, Rayleigh, and Chi-square distributions respectively. Figure 7 shows the mean square errors (MSEs) between a properly exposed portrait and recovered portraits by different types of noises. We find that the qualities and contrasts of images restored by Gaussian, uniform, and Rayleigh noises are quite close, with the Rayleigh case a little bit better, while the image recovered by Chi-square noise seems to have higher contrast, which can also be inferred from Fig. 3.

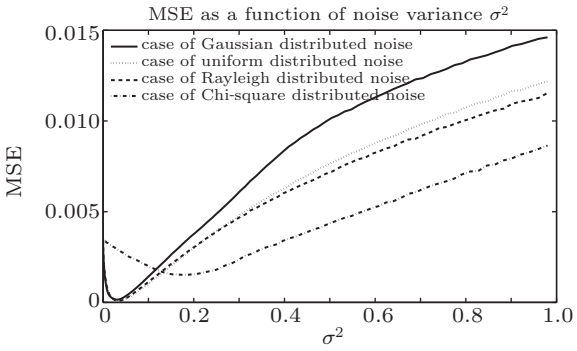


Fig. 7. Mean square errors (MSEs) (y axis) each as a function of noise variance (x axis) under four types of distributions.

Besides severe light conditions, another case where local over exposure often occurs is when flash is used for taking photos. The reflection from a light-coloured surface would be quite strong which might cause unpleasant over exposure. For security, the information such as the plate number of vehicles passing through a check point would be taken down by police cameras. In the lowlight condition flash must be used, which is, however, the main cause of local exposure. Figure 8(a) shows a simulation of a vehicle with the plate number over exposed by flash. The information about the car number is totally lost and cannot be recovered by any tool. If we use the SR system based image sensor rather than conventional one to take down the photo in the same condition, the over exposed information can be preserved. Figures 8(b)–8(e) show the results of SR-based techniques using Gaussian, uniform, Rayleigh, and Chi-square distributions respectively, through which the lost information about the car number is regained. There are slight differences between these results. The performances of the first three distributions are fairly close while in the chi-square case the contrast of the recovered image is much higher. In fact, another simple way to retain car number is to use a higher shutter speed to reduce the exposure duration. The effect is shown in Fig. 8(f). We find that the car number is available, however, the image is so dark that other information is hardly recognizable, such as whether there is anybody in the vehicle, which can be clearly identified in the case of SR technique.



Fig. 8. (a) Images of a vehicle with plate number over exposed by flash; (b), (c), (d), (e) the recovered results by SR based technique using Gaussian, uniform, Rayleigh, and Chi-square distributions respectively; (f) image directly taken down by faster shutter speed.

5. Conclusions

Compared with the dynamic range of human eyes, the dynamic range of an image sensor is rather narrow. It is generally more sensitive to highlight. If an image is over exposed, the information in the highlight would be lost and unable to be recovered with any method. Our proposed noise induced stochastic resonance system is a novel technique to cope with this problem. It is proven in the paper that noise can enlarge the dynamic range of an image. Besides, according to our investigation, the visibility of an image performs a single peak curve as the intensity of specifically added noise grows larger, which demonstrates the effect of stochastic resonance. The lost information can be recovered and reaches the top quality when specified noise is synchronized with the SR system. It is also mentioned in the paper that different types of added noises may result in different outcomes. It is believed that the performances of Gaussian, uniform, and Rayleigh noises are close while the performance of Chi-square noise is a little bit different, which recovers images with higher contrast. The lost information can also be retained by reducing the exposure

duration. However, the dynamic range would not be enlarged with shorter exposure. Thus the image may suffer from another problem: under exposure, which is illustrated in Fig. 8(f). Future work will be done to determine the optimal type and quantity of noises in various over exposure circumstances, and develop a noise reduction algorithm to remove redundant noise and further improve the image quality.

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