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Noise-enhanced recognition under glare conditions

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Abstract—Adding noise has the effect to improve dynamic range. This curious and interesting phenomenon can be found in nonlinear systems and has received much attention since the 1990s. Although the theoretical side of this phenomenon is often discussed, to the best of our knowledge, there has been no successful example in practical situations. The present work demonstrates the effect of adding noise in image recognition in a vehicle environment. A glare situation under which a driver cannot recognize a pedestrian is considered. In our experiments, the dynamic range of the image recognition system is visually confirmed to be increased in terms of the effect "suprathreshold stochastic resonance". This effect is ensured in the analytical discussions. In addition, we derive a framework for tuning the noise variance to enhance the effect.

1. Introduction

Over the last two decades, the role of noise in system enhancement has been discussed in the context of nonlinear physics [1–3]. This curious but interesting phenomenon, which is often referred as stochastic resonance, has been applied in the signal processing field, such as in signal detection theory [4,5], imaging [6], and wireless communication [7]. They are sometimes called as "noise-induced" or "noise-enhanced" schemes [8,9].

Several merits are expected in exploiting noise. In noise-enhanced schemes, the addition of the noise is usually considered [2,3,6]. Such addition realizes amplification of a weak input signal, which means an enhancement of the dynamic range. This effect is beneficial for a fixed device which cannot be tuned nor redesigned. Recently, another merit has been reported. Signals buried in strong noise can be obtained by using a nonlinear device which exhibits noise-enhanced performance. This application is effective in the non-Gaussian noise case, and our proposed method should be employed in such a nonlinear device [5].

The theoretical side of noise-enhanced schemes is often discussed, and the theory is sometimes supplemented by experimental study. Although several research efforts have tried to apply this concept practically, to the best of our knowledge, there has previously been no successful example. The present work demonstrates the performance enhancement by adding noise in a practical vehicle environment. We focus on the glare condition, such those shown in Fig. 1, in which a driver has difficulty seeing a pedestrian wearing white clothes walking in front of a headlight. This pedestrian can be considered as a weak signal (information) buried in the noise of strong light. In this situation, adding noise should improve recognition. Constructing simple image detectors and displays, the effect is investigated visually. To obtain the effect, the noise intensity should be tuned. The performance of the equipment is mathematically analysed, and the optimum noise level is derived.

2. System model and visual results

The system shown in Fig. 1 is built to evaluate the effect of adding noise in the shown glare situation. A white light source plays the role of a headlight. A transparency on which the shape of a pedestrian has been printed is placed in front of the white light source. A walking pedestrian is then represented by moving the transparency from left to right. The light is attenuated by B [lx] in passing through the pedestrian transparency, and this creates a difference with the background light that helps an observer recognize the pedestrian. However, in the present study, we consider strong light. Thus, even if the light is attenuated somewhat, it still remains strong. In the experimental setup, a photodetector (PD) array [10] receives light from the above simulated situation, i.e., the driver's view in Fig. 1. The input light is converted to an electrical signal, the resistor voltage V_R, proportionate to the light strength on the PD array. An LED array [12] displays the situation according to the signal. Because of the strong light, the PD and/or LED should be saturated, and thus the LED array cannot display the shape of the pedestrian. This saturation realizes the fact that the pedestrian cannot be recognized visually by the driver.

As discussed in Sec. 3, the characteristics of the equipment can be varied with the driving voltage of the PD, V_D. The effect of adding noise can be evaluated by the addition of noise to V_D. In the experimental setup, a function generator is used to supply the voltage, since it can output a noisy signal. The driving voltage is $V_D = V_n + V_o$, where V_n is white Gaussian noise with mean zero and variance σ_n^2, and V_o is the offset. This means that the characteristics are probabilistic, and at a certain noise level, it is expected

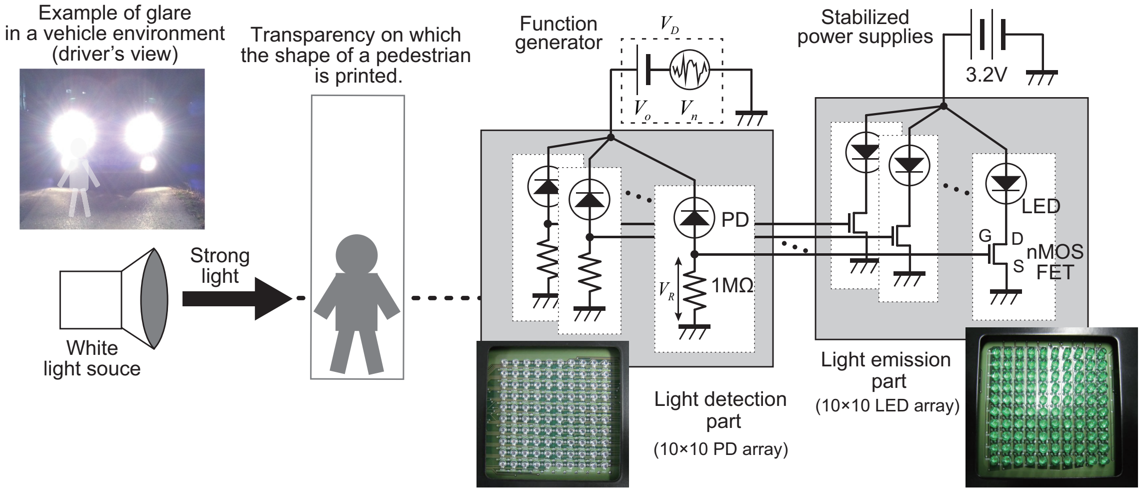
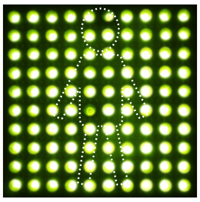
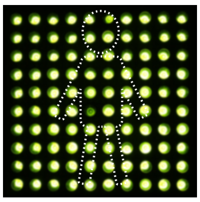


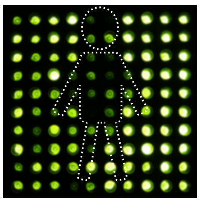
Figure 1: System model and the circuit blocks for generating the noise effect.



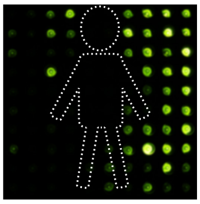
(a) σ_n^2=0.0



(b) σ_n^2=1.0



(c) σ_n^2=22.56



(d) σ_n^2=64.0

Figure 2: Visual perception of the effect of adding noise.

that the saturation is avoided so that the shape will be illuminated on the LED array.

The visual results are shown in Fig. 2. The input light strength is set to be 150 [lx] and is attenuated by 70 [lx] in passing through the pedestrian transparency. In this situation, in the no-added-noise case, as shown in Fig. 2(a), the LED array cannot display the shape of the pedestrian at all. Figures 2(b)-(d) are the results in the case of adding noise. In these figures, the noise variances are varied since the effect of adding noise depends on the noise variance [1–3]. In Fig. 2(c), the shape can be found. Figure 2(b) is the result with a small noise, σ_n^2=1.0; here, there is no difference with Fig. 2(a) in terms of recognition. With a large value of σ_n^2=64.0, the right-hand side of the shape may be identified, but the left-hand side is still missing. In the next section, the device performances are analysed to explain the results shown in Fig. 2. One may think that it is hard to understand the effect in these figures. In the presentation, the authors show the movie to help the understanding.

3. Performance analysis and numerical results

3.1. Basic performance

In this section, the performances in the no-added-noise case are discussed to explain the operating principles and point out under what conditions saturation occurs. In the equipment of the experimental setup, when light is irradiated on the PD array, the PD current increases and the voltage on the resistor V_R increases. In this way, V_R is proportional to the input light strength. An LED array displays the input light strength at each point of the PD array, and the illumination is proportional to V_R.

Figure 3 shows the measured V_R values as a function of the input light strength x [lx]. Note that the driving voltage V_D does not contain a noise component, i.e., $V_n = 0$ and $V_D = V_o$. Using an actinometer, the input light strength is measured at a point below the PD array. The strength varies with the distance between the white light source and the PD. From Fig. 3, there are two types of performance, that in response region $\mathfrak{R}_L$ and that in saturated region $\mathfrak{R}_S$. In this sense, our system is nonlinear. In the saturated case, the voltage V_R is almost constant, so that the LED array cannot display the shape of the pedestrian. An increase in the driving voltage enables V_R to attain a response. For example, in the case of x=100 [lx], although V_R is saturated with respect to input light strength at V_D = 2.0 [V], V_R is proportional to V_D up to V_D = 5.0 [V]. In this sense, saturation does not occur in the PD.

The performance in the response region is independent of the driving voltage, which can be approximately expressed by the quadratic function $L(x) = ax^2+bx+c$, where $a = -3.0 \times 10^{-5}$, $b = 0.0425$, and $c = -0.1378$. This function, which is plotted as red points in Fig. 3, is well fitted to the response. The saturated performance is constant with respect to the strength x and varies only with the driving

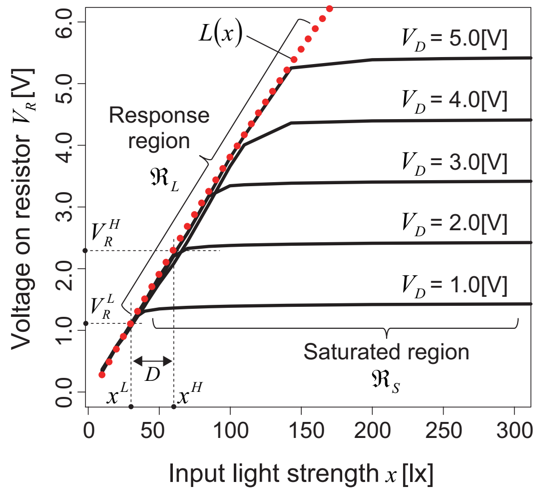


Figure 3: Resistor voltage V_R vs. input light strength x.

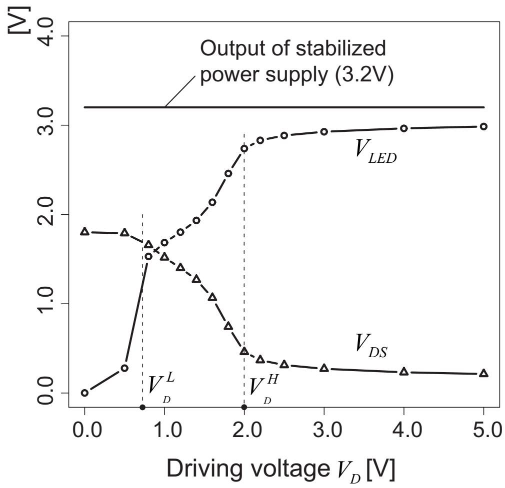


Figure 4: Performances of V_{DS}, V_{LED} for V_D.

voltage, to which it is proportional. This means that the function $S(V_D) = V_D + \tilde{V}_o$ can represent the performance, where $\tilde{V}_o$=0.393 [V]. Therefore, the voltage V_R can be

$$V_R = H(x; V_D) = \begin{cases} L(x) = ax^2 + bx + c & (x < x_0) \\ S(V_D) = V_D + \tilde{V}_o & (x \geq x_0) \end{cases} \quad (1)$$

where x_0 is defined as the input light strength which satisfies the relation $L(x_0) = S(V_D)$.

The performance of the light emission component is next discussed. Figure 4 depicts the measured performance of drain-source voltage V_{DS} in a MOSFET and the voltage V_{LED} on an LED. For $V_{DS} \in [0.0, 2.0]$, the output current is linear [11]. From Fig. 4, the equipment works in that region, by which the output of the MOSFET is not saturated. The voltage V_{LED} linearly increases after tuning at V_{LED} = 0.7 [V]. The value is saturated when the driving voltage is larger than 2.0 [V] [12]. Considering that the PD is not saturated in this region, it can be stated that the output of the LED is saturated and so the LED does not display the input situation. Let V_D^L and V_D^H be the minimum and maximum voltages at which the LED can linearly respond, respectively.

The dynamic range in the equipment can be calculated based on Fig. 3 and Fig. 4. $V_R^H = S(V_D^H)$ and $V_R^L = S(V_D^L)$ are defined as the maximum and minimum voltages, respectively, on the resistor at which the LED can respond. The response function $L(x)$ can give the lower limit and the upper limit of the input light strengths $x^L = L^{-1}(V_R^L)$ and $x^H = L^{-1}(V_R^H)$ corresponding to the minimum and maximum voltages, respectively. Then, the dynamic range is calculated as $D = x^H - x^L$. In our system, $V_D^L \approx 0.63$ [V] gives V_R^L=1.02 [V], and x^L=27.90 [lx]. In a similar way, x^H=x_0=62.29 [lx], which gives a dynamic range of D=34.39 [lx] without the addition of noise.

3.2. Performance in the case of adding noise

Performance for the case of adding noise is evaluated mathematically and numerically in this section. From Fig. 4, an LED can respond only when the driving voltage is smaller than 2.0 [V]. This means that a PD can linearly detect an input light x which is less than x_0, i.e., the voltage V_R should fall within the region from V_R^L to V_R^H. Adding noise can realize such voltages, and the PD should detect the stronger input light. To demonstrate this point, the average performance of the voltage V_R is analysed.

Considering that the driving voltage contains a noise component, i.e., $V_D = V_n + V_o$, the average performance can be obtained as

$$\bar{V}_R(x; \sigma_n^2) = \int_{-\infty}^{\xi(x)} S(V_D)P(V_D)dV_D + \int_{\xi(x)}^{+\infty} L(x)P(V_D)dV_D \quad (2)$$

where $P(V_D)$ is the probability of the voltage V_D, which follows a Gaussian distribution with mean V_o and variance σ_n^2, and $\xi(x)$ is the driving voltage at which the response $L(x)$ equals the saturated performance $S(V_D)$, i.e., where the relation $L(x) = S(\xi(x))$ holds. A numerical example is described in Fig. 5. The mean of the driving voltage V_o is set to be 2.0 [V], and three curves corresponding to different noise variances are shown in red. The performance indicated by the black line is that in the no-added-noise case.

From Fig. 5, the upper limit of the input light strength is proportional to the noise variance. The lower limit also increases with the input light strength, but more slowly. This means that the response region is enhanced and so the dynamic range is improved. For example, in the case of σ_n^2=1.0, the lower limit is the same as the one without adding noise, i.e., 27.90 [lx]. The upper limit is 82.90[lx], so that the dynamic range is 82.90-27.90=55.0[lx]. Compared to the case without adding noise, the range is im-

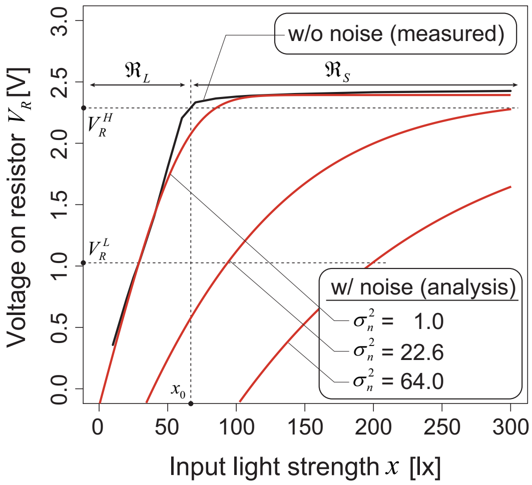


Figure 5: Average performance of the resistor voltage.

proved by 10.61[lx].

Figure 5 shows that the dynamic range is improved as the increase of the noise variance. However, from Fig. 2, this is not true because there is an optimum noise variance at which recognition is most enhanced. The reason is that the lower limit of the input light strength becomes large compared to the input light itself so that the illumination of the LED disappears. As the increase of the noise variance, the dynamic range is enhanced, but the lower limit moves to the high strength region and the PD cannot detect the weak input light. In this sense, the optimum noise variance is the level at which the lower limit equals to the input light strength. Actually, in the system of Fig. 1, the attenuated light should be larger than the lower limit. The strength is 80[lx], and from Fig. 5, the lower limit agrees with it when σ_n^2=22.6. In this case, the recognition is most enhanced as shown in Fig. 2.

4. Conclusion

In the present work, the effect of adding noise in image recognition is demonstrated in a practical vehicle environment. A glare situation is considered, and adding noise within the equipment improves the ability to recognize a pedestrian. Discussions in Sec. 3 make clear the equipment problems and the advantage of adding noise, i.e., improvement of the dynamic range. A disadvantage of adding noise also appears, in that the lower limit of the input light strength is decreased by an increase in noise. In this sense, the noise variance should be tuned. The optimum variance is derived in our discussion, which should be helpful for equipment design. The above points are visually confirmed as shown in Fig. 2.

One of the conventional methods applied in this situation is automatic gain control (AGC). In AGC, the dynamic range is automatically adjusted to solve the recognition problem under saturated conditions. Our method of adding noise has the additional merit of enhancing the dynamic range.

Generally, saturated performance can be modelled as eq. (1). The concept of adding noise can be applied to various devices and the performance is fully expressed as eq. (2). In this sense, the present work makes a contribution beyond that to the recognition problem, and our design framework for noise variance should be a good reference for other works.

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