Recovery from low light level images

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ABSTRACT

The result of detecting in low light level are images with only a small number of photopulses. Only the pixels in which arrive the photopulse have an intensity value different from 0.

The work presents an easy procedure for simulating low light level images by taking an standard well illuminated image as a reference. The images so obtained are composed by a few illuminated pixels on a dark background. The number of illuminated pixels is less than the 1% of the total pixels number, and hence it is difficult to recognize the original object.

A procedure for enhancement and recovery the original image is described and applied to low light level images previously simulated.

The result is a visual experiment, easy to be performed (using a personal computer and a frame grabber), which state the statistical nature of light.

1.- PHOTON-LIMITED IMAGES

At low levels of illumination, an input scene can be described in a binomial form. The detected image is composed of a set of photo-pulses distributed over a dark background, and hence, can be represented as a collection of Dirac-delta functions:

$$\hat{I}(\mathbf{r}, t) = \sum_{k=1}^{N} \delta(\mathbf{r} - \mathbf{r}_k(t)) \qquad (1)$$

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where r_k represents the spatial coordinates of the k-th detected photo-pulse and N is the total number of detected photo-pulses.

If the photo-pulses are collected by a detector of area A for a fixed time interval T, the conditional probability distribution for detecting N photo-pulses in the time interval [t,t+T] is an inhomogeneous Poisson process given by[1]:

$$P(N) = \frac{1}{N!}\left[\int_t^{t+T} dt' \int_A \lambda(\mathbf{r}, t')d\mathbf{r}\right]^N \exp\left[-\int_t^{t+T} dt' \int_A \lambda(\mathbf{r}, t')d\,\mathbf{r}\right] \qquad (2)$$

in which $\lambda(\mathbf{r},t) = \eta I(\mathbf{r},t)/h\nu$ where η is the quantum efficiency of the detector, $I(\mathbf{r},t)$ is the classical image irradiance, h is Planck's constant and ν the incident light frequency.

In those cases in which $I(\mathbf{r},t)$ does not fluctuate significantly, the ensemble average produces the following observable counting distribution:

$$P(N) = \frac{\bar{N}^N}{N!} e^{-\bar{N}} \qquad (3)$$

where:

$$\bar{N} = \frac{\eta T}{h\nu} \int_A I(\mathbf{r})d\mathbf{r} \qquad (4)$$

It can also be seen that the probability density function for photo-pulse coordinates is given by [2]:

$$P(\mathbf{r}) = \frac{I(\mathbf{r})}{\int_A I(\mathbf{r}')\,d\mathbf{r}'} \qquad (5)$$

2.-SIMULATION OF PHOTON-LIMITED IMAGES

To obtain photon-limited images from the input scene in an actual experiment it is necessary to use an image intensifier.

This is an expensive and sophisticated instrument. However it is easy to simulate photon-limited images once an image has been obtain with an standard CCD camera. Hence simulation will be the procedure used to obtain photon-limited images more easily.

The previous section described the statistical behaviour of photon-limited images. This will now be used in the simulation procedure as follows.

- The value of every point of the simulated image is obtained by using a subroutine (GGPON) which generates Poissonian distributed random values.
- The parameter introduced in the Poissonian generator is the intensity pixel value of the image obtained by the CCD camera once this value has been normalized.
- The normalization parameter is defined as $N_p = N_s/I_T$, where N_s is the mean value of the number of photo-pulses in the simulated image and I_T is the total intensity of the input image.

This simulation method allows us to obtain images with the same characteristics as those taken with a low light level camera.

Fig. 1 shows an image obtained with the CCD camera and Fig. 2 shows the results of the simulation by using the procedure described above. The simulated photon-limited image was obtained for a mean value of 500 photo-pulses.

3.-IMAGE RECONSTRUCTION

The input scene is determined by a function, $I(\mathbf{r},t)$, which varies continuously in a wide range of values as a function of the position. Our goal is to obtain a function as similar to the input scene as possible by starting from a low light level image which is described by Eq(1). To do this, important differences must be considered. In low light level images only a small number of the detector points have a value different from zero and the only two intensity value allowed for these points is 1. As a result, two problems arise when recovering the intensity which describes the input scene. First, it is necessary to give values different from zero to an important number of detected image points and, second, these intensity values must follow a distribution similar to that of the input scene.

The procedure followed for obtaining the reconstructed image $I(\mathbf{r})$ is based on the assumption that the input scene is composed of regions of constant intensity. A square mask of side M is centered on point $\mathbf{r}_k$ of the simulated image. The intensity value of this point of the reconstructed image is obtained by averaging the number of photo-pulses in the simulated image over the points contained in the mask.

$$I_R(\mathbf{r}_k) = \frac{1}{M^2} \sum_{\xi=\frac{-(M-1)}{2}}^{\frac{M-1}{2}} \sum_{\zeta=\frac{-(M-1)}{2}}^{\frac{M-1}{2}} I(x_k+\xi, y_k+\zeta) \qquad (6)$$

This procedure is repeated for each point of the image.

The probability density of detecting one photo-pulse at a point of coordinates $\mathbf{r}$, in low intensity, is given by:

$$P(1) = < I(\mathbf{r})\, e^{-I} > \approx < I(\mathbf{r}) > \qquad (7)$$

If we suppose that the intensity is constant all over the mask region, an estimation of P(1) over the mask will be :

$$P(1) = \text{number of 1's in the mask} / M^2 \qquad (8)$$

Hence $I_R(\mathbf{r}_k)$, described by Eq.(6), coincides with P(1) and therefore with an estimation of $< I(\mathbf{r}) >$.

The assumption of constant intensity in the mask is only an approximation that is not clearly fulfilled along the region edges. However, the results obtained confirm that this approximation can be considered as fairly good. The mask side M must be small enough to maintain this approximation, but for large values of M , the estimation performed in Eq.(8) will be better. Hence, it is necessary to find the appropriate mask side for every each image. The result of passing a mask over the low light level image depends on the mask side. Fig.(3) and (4) show the results obtained with mask side 5 and 7 respectively. In these images a human face can be recognized more easily than in Fig.(2).

4.-RECONSTRUCTED IMAGE HISTOGRAM

In a mask with side M, we have M^2 pixels in which the intensity function can have only two possible values (0 or 1). Hence the probability of having n photo-pulses in the mask is given by a binomial distribution:

$$P_I(n) = \binom{M^2}{n} p^n (1-p)^{M^2-n} \tag{9}$$

where p is the ratio:

$$p = \text{number of positive cases} / M^2 = \langle I(\mathbf{r}) \rangle \tag{10}$$

which is the mean intensity value in the mask, as defined in Eq.(8).

If the input scene is composed of R regions with a different mean intensity value (I_j), the probability of having n photo-pulses in a low light level image will be:

$$P(n) = \sum_{j=1}^{R} P(I_j) P_{I_j}(n) \tag{11}$$

where:

$$P(I_j) = \text{number of pixels with intensity } I_j \,/\, \text{total number of pixels} \tag{12}$$

Eq.(11) determines the histogram shape, which will decrease abruptly because the $\langle I(\mathbf{r}) \rangle$ values are very small. Since the input scene may have quite different histogram shapes, it will be necessary to eliminate the statistical dependence shown in Eq.(11).

5.-HISTOGRAM EQUALIZATION

The histogram described in Eq.(11) has two important differences with respect to the input histogram. Its shape is controlled by the statistical nature of the detection, and the maximum value of n is small compared with the maximum gray level of the input scene. These problems can be solved by performing an equalization of the experimental histogram[3].

Equalization is an operation that changes any histogram into a flat one. This allows elimination of the statistical dependence and the whole gray level range to be filled.

The equalized histogram is not equal to that of input scene, but it improves the results in a wide range of cases. The reason is that a flat histogram reproduces a general histogram better than any other does.

Fig. 5 and 6 show equalization of Fig. 3 and 4 respectively. Comparison techniques, not described in this paper, can be used to show that Fig. 5 and 6 fit the input image better than Fig. 3 and 4.

REFERENCES

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Fig.1: Reference Image.

Fig.2: Simulation result.

Fig.3: Result of passing a mask (side 5) over Fig. 2.

Fig.4: Result of passing a mask (side 7) over Fig. 2.

Fig.5: Image obtained after histogram equalization of Fig.3.

Fig.6: Image obtained after histogram equalization of Fig.4.