

## Introduction

We study a new image device called gigavision camera [1] or the gigapixel digital film camera [2]. The main differences between a conventional and a gigavision camera are that the pixels of the gigavision camera are binary and orders of magnitude smaller. A gigavision camera can be built using standard memory chip technology, where each memory bit is designed to be light sensitive. A conventional gray level image can be obtained from the binary gigavision image by low-pass filtering and sampling.

The main advantage of the gigavision camera is that its response is non-linear and similar to a logarithmic function, which makes it suitable for acquiring high dynamic range scenes. The larger the number of binary pixels considered, the higher the dynamic range of the gigavision camera will be.

## Camera architecture[1]

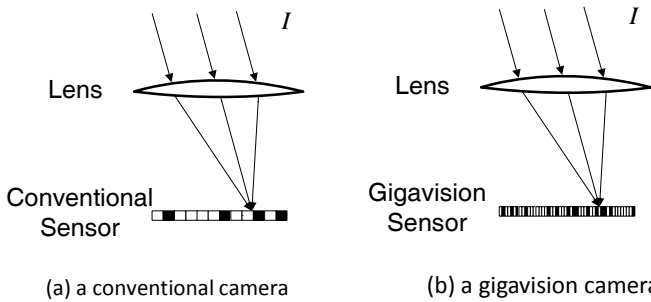


Figure 1: Simplified architecture of a conventional camera and a gigavision camera. The incident light is focused by the lens and then impinges on the image sensors.

## Pixel model

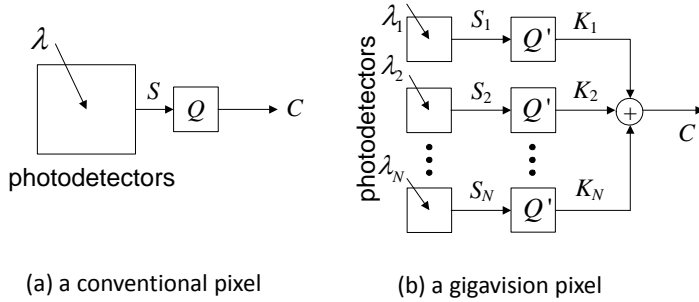


Figure 2: Simplified block diagram of a conventional pixel and a gigavision pixel. For the conventional camera, the incident photons first are converted to the electrical signal  $S$ , then quantized by a multi-level quantizer. For the gigavision camera, the electrical signal  $S_i$  is quantized by a one-bit quantizer with threshold  $T$  and the pixel value  $C$  is the sum of the  $N$  pixels.

## Response function and estimation error variance

When the threshold is set to  $T = 1$  the response function of gigavision camera is

$$E[C] = N \left( 1 - e^{-\frac{\lambda}{N}} \right)$$

The sum  $c$  of active pixels is used to estimate the parameter  $\lambda$ , which corresponds to light intensity. This is obtained by using a maximum likelihood estimator,

$$\hat{\lambda} = \arg \max \binom{N}{c} p_{\lambda}^c (1 - p_{\lambda})^{N-c}$$

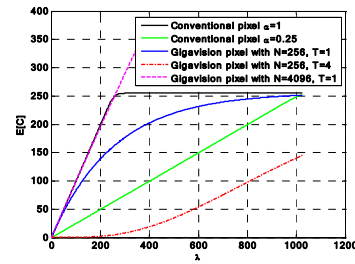


Figure 3: Response function of a conventional pixel and a gigavision pixel. The quantizer of the conventional pixel has  $N = 256$  levels and parameters  $\alpha = 1$  and  $\alpha = 0.25$ . For the gigavision pixel the thresholds are  $T = 1$ , and  $T = 4$ , and the oversampling factors are  $N = 256$ , and  $N = 4096$ .

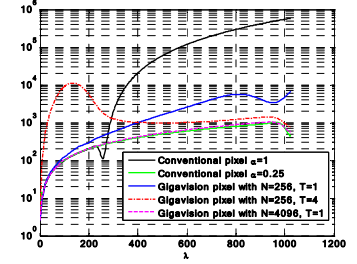


Figure 4: Estimation error variance of a conventional pixel and a gigavision pixel. The quantizer of the conventional pixel has  $N = 256$  levels and parameters  $\alpha = 1$  and  $\alpha = 0.25$ . For the gigavision pixel the thresholds are  $T = 1$ , and  $T = 4$ , and the oversampling factors are  $N = 256$ , and  $N = 4096$ .

## Influence of the threshold[3]

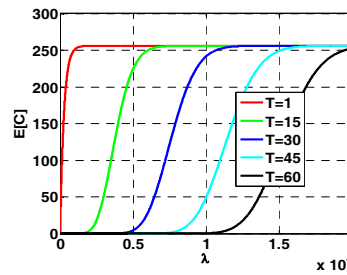


Figure 5: Response function of a gigavision pixel with threshold  $T = 1, 15, 30, 45, 60$ , oversampling factor  $N = 256$ .

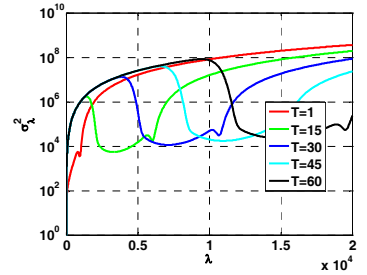


Figure 6: Estimation error variance of a gigavision pixel with threshold  $T = 1, 15, 30, 45, 60$ , oversampling factor  $N = 256$ .

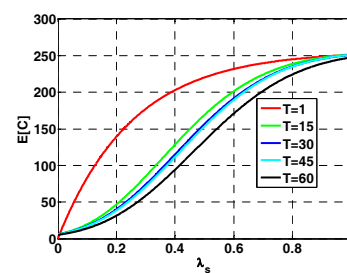


Figure 7: Response function for different thresholds. The curves are obtained by setting the exposure time and the added light in order to cover the value  $E[C]$  in the range  $N \times 0.02$  and  $N \times 0.98$ .

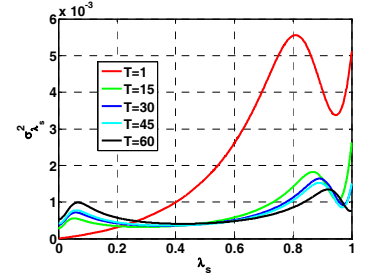


Figure 8: Estimation variance for different thresholds. The curves are obtained by setting the exposure time and the added light in order to cover the value  $E[C]$  in the range  $N \times 0.02$  and  $N \times 0.98$ .

**Conclusion:** low light intensity, smaller  $T$  is better; strong light intensity larger  $T$  is better.

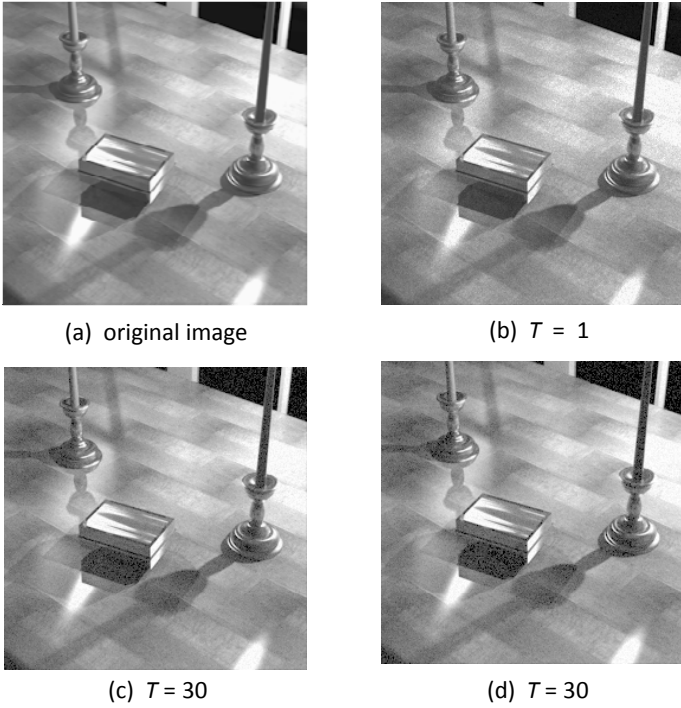


Figure 9 :Original image and images taken by gigavision sensor with different thresholds.

### Optimal reconstruction algorithm[4]

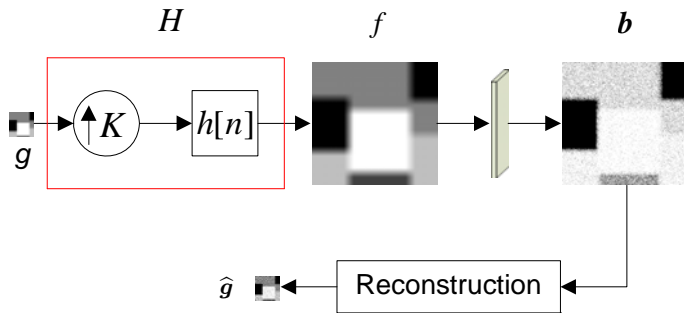


Figure 10: The model for the gigavision camera.

For threshold  $T = 1$ :

$$f = Hg \quad \begin{cases} \mathbb{P}(b_i = 0) = e^{-f_i(g)} = e^{-h_i^T g} \\ \mathbb{P}(b_i = 1) = 1 - e^{-f_i(g)} = 1 - e^{-h_i^T g} \end{cases}$$

Maximum likelihood estimator:

$$\begin{aligned} \hat{g} &= \arg \max_g \mathbb{P}(\mathbf{b}; g) \\ &= \arg \max_g \prod_{n=1}^N \left( (1 - \mathbf{b}[n])e^{-f_n(g)} + \mathbf{b}[n](1 - e^{-f_n(g)}) \right) \\ &= \arg \min_g - \sum_{n=1}^N \ln \left( (1 - \mathbf{b}[n])e^{-f_n(g)} + \mathbf{b}[n](1 - e^{-f_n(g)}) \right) \end{aligned}$$

**Theorem:** negative log-likelihood function is convex function, **optimal solution** can be obtained.

Maximum likelihood estimator for multiple exposures:

$$\begin{aligned} \hat{g} &= \arg \max_g \mathbb{P}(\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_S; g) \\ &= \arg \min_g - \sum_{s=1}^S \sum_{n=1}^N \ln \left( (1 - \mathbf{b}_s[n])e^{-f_n(g)} + \mathbf{b}_s[n](1 - e^{-f_n(g)}) \right). \end{aligned}$$

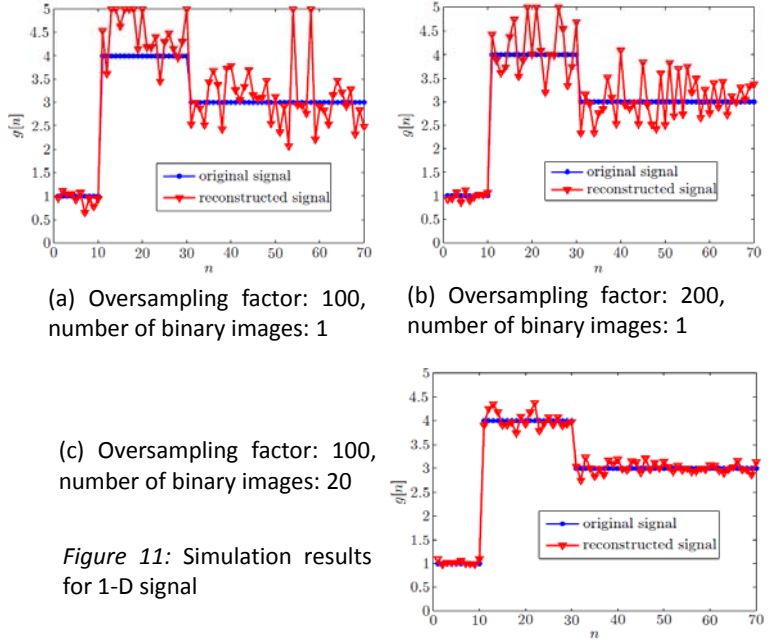


Figure 11: Simulation results for 1-D signal

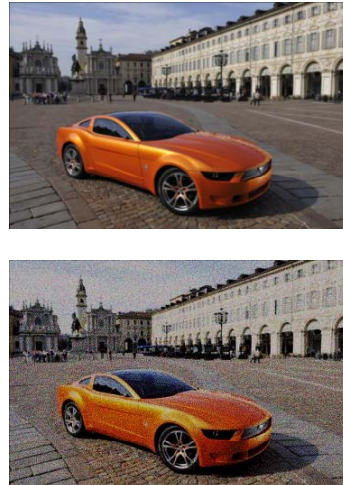


Figure 12: Simulation results for images

### Reference

- [1] L. Sbaiz, F. Yang, E. Charbon, S. Süsstrunk, and M. Vetterli, The gigavision camera, in IEEE International Conference on Acoustics, Speech and Signal Processing, Taipei, April 2009, pp. 1093-1096.
- [2] E. R. Fossum. Gigapixel digital film sensor. (invited) in *Nanospace Manipulation of Photons and Electrons for Nanovision Systems, The 7th Takayanagi Kenjiro Memorial Symposium and the 2nd International Symposium on Nanovision Science*, University of Shizuoka, Hamamatsu, Japan, October 25-26, 2005.
- [3] F. Yang, L. Sbaiz, E. Charbon, S. Süsstrunk, and M. Vetterli, On pixel detection threshold in the gigavision camera, in *IS&T/SPIE Electronic Imaging, Digital Photography V*, San Jose, Jan. 2010.
- [4] F. Yang, L. Sbaiz, Y. M. Lu, and M. Vetterli, An optimal algorithm for reconstructing images from binary measurements, in *IS&T/SPIE Electronic Imaging, Computational Imaging*, San Jose, Jan. 2010.