Photocurrent Estimation from Multiple Non-destructive Samples in CMOS Image Sensor

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Introduction

- Dynamic range is a critical figure of merit
  - Ratio of the largest to the smallest detectable photocurrent
  - CMOS imagers have lower dynamic range than CCDs due to higher readout noise
- Integration of CMOS sensor and processing opens up many possibilities for enhancing dynamic range

Dynamic Range Enhancement Using Multiple Samples

- **Yadid-Pecht'97, Yang'99**
  - Multiple images captured within exposure time
  - Scale each pixel's last sample and combine into a single high dynamic range image
  - Achieves higher SNR than other schemes

- **Limitation**
  - Readout noise remains the same — same low illumination performance
  - Dynamic range extended only at high illumination

Approach

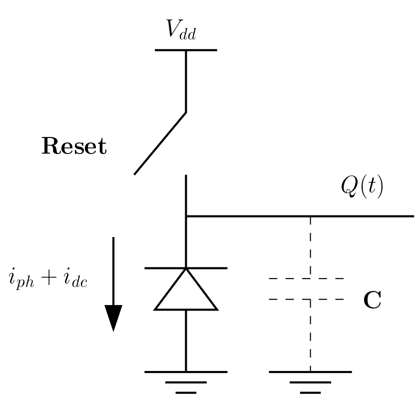
- **Use linear least mean square estimator (LLMSE) to estimate the photocurrent from multiple samples**
  - Weighted *averaging* of samples to reduce readout noise
  - Extends dynamic range and improves SNR at low illumination end

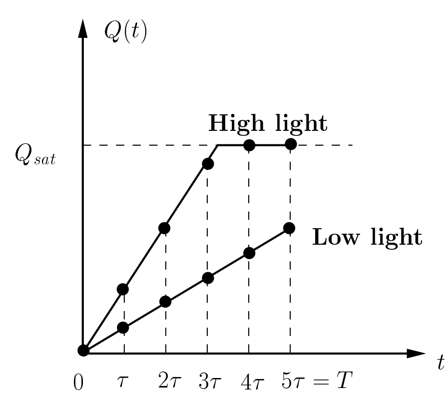
- **Find algorithm that is feasible for sensor system-on-chip integration:**
  - Small memory
  - Low computational complexity

Outline

- **Sensor model and problem formulation**
- **Photocurrent estimation algorithms**
  - **Non-recursive algorithm**
  - **Recursive algorithm**
- **Simulation results**
- **Conclusion**

CMOS Image Sensor Model





Conventional Sensor Operation Model

$$Q(T) = \begin{cases} (i_{ph} + i_{dc})T + U(T) + V(T) + C, & \textbf{for } Q(T) \leq Q_{sat} \\ Q_{sat}, & \textbf{otherwise} \end{cases}$$

– Q_{sat}, **well capacity**

– $U(T) \sim \mathcal{N}(0, q(i_{ph} + i_{dc})T)$, **shot noise**

– $V(T)$, **readout noise, zero mean and variance** σ_V^2

– $C \sim \mathcal{N}(0, \sigma_C^2)$, **reset and FPN noise**

SNR is expressed as

$$\textbf{SNR}(i_{ph}) = 10 \log_{10} \frac{(i_{ph}T)^2}{q(i_{ph} + i_{dc})T + \sigma_V^2 + \sigma_C^2}$$

Sensor Model for Multiple Samples

- **Assuming** $n+1$ **photocharge samples uniformly captured in [0,T], let** $i = i_{ph} + i_{dc}$**, the** k**th sample**

$$Q_k = ik\tau + \sum_{j=1}^{k} U_j + V_k + C, \ \textbf{for } 0 \leq k \leq n,$$

– V_k: **readout noise of the** k**th sample**

– U_j: **shot noise during** $((j-1)\tau, j\tau]$

– **The noise terms all zero mean, independent**

$$\begin{aligned} E(V_k^2) &= \sigma_V^2 > 0, \\ E(U_j^2) &= \sigma_U^2 = qi\tau, \\ E(C^2) &= \sigma_C^2 \end{aligned}$$

Problem Formulation

- **Use linear least mean square estimation (LLMSE) to derive the *optimal* weights, *i.e.*, Given $Q_0, Q_1, \ldots, Q_k$, find coefficients $b_0, b_1, \ldots, b_k$ such that**

$$\hat{I}_k = \sum_{j=0}^{k} b_j Q_j,$$

minimize

$$\Phi_k^2 = E(\hat{I}_k - i)^2$$

subject to

$$E(\hat{I}_k) = i$$

Photocurrent Estimation

- **Define photocurrent sample $\tilde{I}_k$ as:**

$$\tilde{I}_k = \frac{Q_k - wQ_0}{k\tau}, \text{ for } 1 \le k \le n$$

where

$$w = \frac{\sigma_C^2}{\sigma_C^2 + \sigma_V^2}$$

- **Note that $\tilde{I}_k$ represents a *weighted* CDS operation**
  - **The weighting factor minimizes additional readout noise due to CDS**

Optimal Estimate

- **Estimate i with k samples**

$$\hat{I}_k = \mathbf{A}_k \tilde{\mathbf{I}}_k,$$

where

$$\mathbf{A}_k = [a_1^{(k)}\ a_2^{(k)}\ \ldots\ a_2^{(k)}], \text{ and } \tilde{\mathbf{I}}_k = [\tilde{I}_1\ \tilde{I}_2\ \ldots\ \tilde{I}_k]^T$$

- **Discussion**
  - **With no reset and readout noise, best estimate is the last sample $\tilde{I}_k$, *i.e.*, $\mathbf{A}_k = [0\ \ldots\ 0\ 1]$**
  - **With reset and readout noise, simple averaging, *i.e.*, $\mathbf{A}_k = [\frac{1}{k}\ \ldots\ \frac{1}{k}]$, does not result in good estimate**

Non-recursive Algorithm

- **The optimal coefficient vector $\mathbf{A}_k$ is given by**

$$\mathbf{A}_k = -(\frac{\sigma_U^2}{\tau^2} M_k + \frac{\sigma_V^2}{\tau^2}(T_k + wD_k F_k^T))^{-1} \frac{\lambda}{2} L_k$$

where M_k, D_k, F_k, L_k, T_k are known matrices and λ is the Lagrange multiplier for the unbias constraint

- **The above solution cannot be expressed in a recursive form**
  - **Requires the storage of all $\tilde{I}_k$s and inverting a $k \times k$ matrix**
  - **Not practical!**

Recursive Algorithm

- **Restrict ourselves to recursive estimate of the form**

$$\hat{I}_k = \hat{I}_{k-1} + h_k(\tilde{I}_k - \hat{I}_{k-1}),$$

where

  - $\hat{I}_{k-1}$, **estimate at** $(k-1)\tau$
  - $\tilde{I}_k$, **new sample at** $k\tau$
  - h_k, **innovation gain**

- **The coefficient** h_k **can be found using the unbias constrain and solving**

$$\frac{d\,\Phi_k^2}{d\,h_k} = \frac{d\,E(\hat{I}_k - i)^2}{d\,h_k} = 0$$

Recursive Algorithm (Cont'd)

- **Recursive solution**

$$h_k = \frac{\Phi_{k-1}^2 - \frac{(k-1)}{k}\Theta_{k-1} + \frac{h_{k-1}\sigma_V^2}{k(k-1)\tau^2}}{\Phi_{k-1}^2 - \frac{2(k-1)}{k}\Theta_{k-1} + \frac{2h_{k-1}\sigma_V^2}{k(k-1)\tau^2} + \Delta_k^2}$$

- **In the above solution,** Θ_k, Φ_k **can be calculated recursively as well**

- **At each estimation iteration, only need three parameters** h_k, Φ_k, Θ_k, **and the old estimate** $\hat{I}_{k-1}$
  - **Small memory and low computation per pixel**

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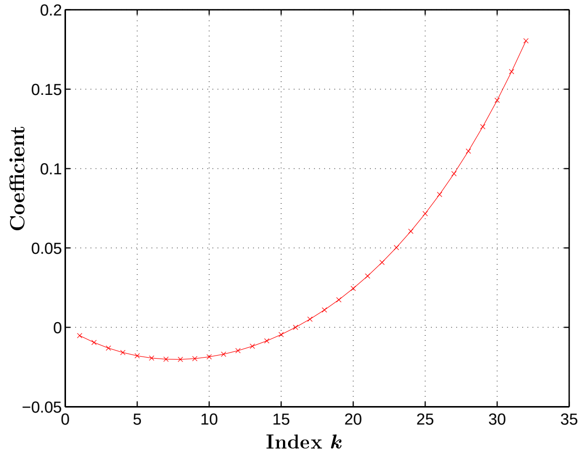
Sensor Parameters

Well capacity:	$Q_{sat} = 18750$ **e-,**
Diode area:	**5μm x 5μm,**
Quantum efficiency:	**QE = 30%**
Dark current:	$i_{dc} = 0.1$ **fA**
Readout noise RMS:	$\sigma_V = 60$ **e-,**
Reset noise RMS:	$\sigma_C = 62$ **e-,**
Exposure time:	$T = 32$ **ms,**
Number of samples:	$n = 32$

Optimal Coefficients

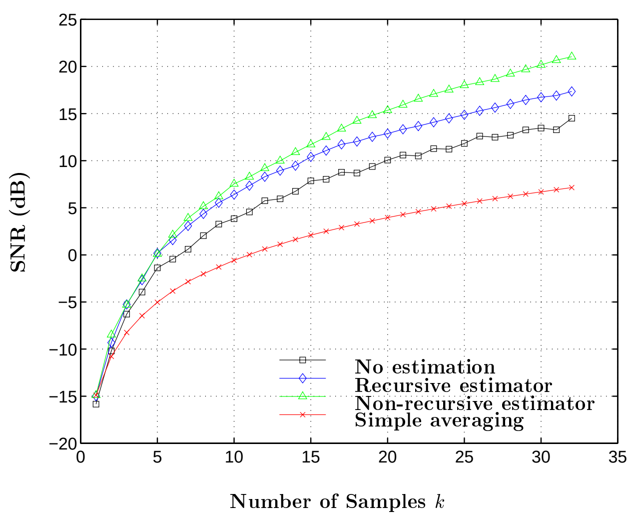
The optimal coefficients a_k used in

$$\hat{I}_n = \sum_{k=1}^{n} a_k \tilde{I}_k,$$

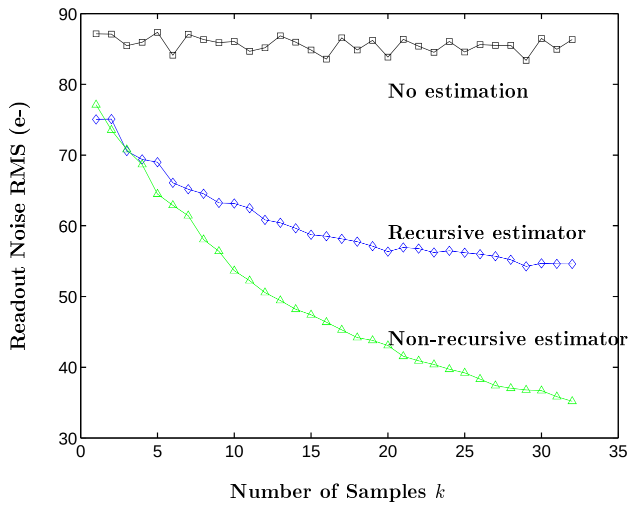


SNR vs. Number of Samples

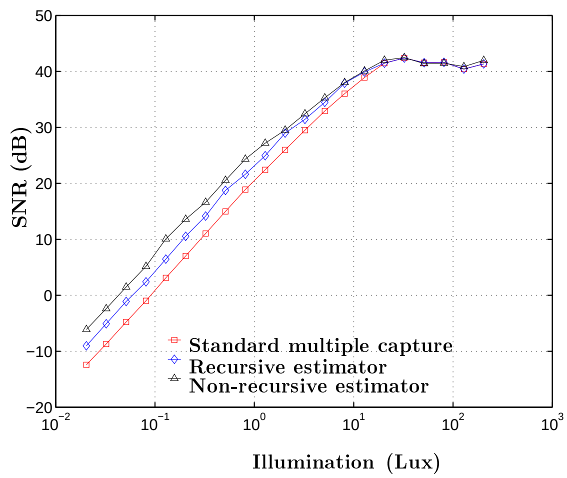
Assume $i_{ph} = 2\text{fA}$



Equivalent Readout Noise RMS



SNR vs. Illumination



- **Maximum illumination: 8Lux $\longrightarrow$ 204Lux (30dB)**
- **Minimum detectable: 0.05Lux $\longrightarrow$ 0.02Lux (8dB)**
- **SNR increase 6dB**

Conclusion

- Photocurrent estimation algorithms using LLMSE
  - Reduce sensor readout and reset noise
  - Enhance sensor SNR
  - Extend sensor dynamic range at the low illumination end
- Our algorithm operates locally and recursively
  - Small memory and computation per pixel
  - Each pixel's photocurrent is independently estimated
- Suited to be implemented in a single chip imaging system