Wide Dynamic Range PSD Algorithms and Their Implementation for Compressive Imaging

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***Abstract*—Planned Sensor Distortion (PSD) is a compression method that quantizes shifted signal with low bit depth. In this paper, we analyze the dynamic range loss issue in the PSD algorithm and propose two novel methods to overcome this issue: a blocked PSD, which divides the image into sub-blocks that adapt to pixel values, and an auto-reset PSD, which utilizes Markov property to recover a high dynamic range image from the modulo image. Simulation on a 3-bit depth image of indoor environment shows PSNR of $35.7dB$ and $35.0dB$ respectively after reconstruction using our algorithms. Thereafter, two different implementations for PSD are proposed, introducing shifts at either reset phase or readout phase. These circuits are then extended to be compatible with our proposed algorithms. Finally, simulation results using 0.18um GlobalFoundries process validate our designs. Spontaneous power optimization of ADC and transmission, hardware friendly feature, and the ability of high quality imaging make our compression method promising.**

I. Introduction

Wireless Multimedia Sensor Networks (WMSNs) have attracted growing research interest in the past decades [1]. Power consumption is a fundamental concern in WMSN design, which mainly comes from sensor power and transmission power. Since power of transmission is two orders of magnitude higher than that of state-of-art image sensors [2], bandwidth reduction is crucial for low power WMSNs. To improve net power savings, the compression process should consume less power than the reduced power for transmission [3]. In order to achieve this trade-off, various on-chip compression algorithms have been proposed [4]. However, most of them provide low image quality or produce large hardware overhead.

Possessing potentials to provide better image quality with little compression overhead, Wan [5] proposed a PSD algorithm (Planned Sensor Distortion) utilizing the locality characteristic in natural images, by introducing a predefined distortion into the raw image and then quantizing the image with low bit depth resolution. The image can be then reconstructed with higher quality by undistorting shifts and deducing the true values from adjacent pixels. This algorithm reduces the raw data amount from the image sensor thereby reduces transmission power, moreover, it reduces the power consumption of the image sensor readout (interface circuits and ADCs) because now the required bit number for quantization is much lower. However, this method results in noticeable dynamic range (DR) loss. In order to solve the DR loss issue, we propose two algorithms—blocked PSD and auto-reset PSD: blocked PSD adapts to illumination intensity for each sub-block while auto-reset PSD reconstructs ultra-high dynamic range, which is based on the work of modulo sensor [6]. The structure similarity index measure (SSIM) improves by 21.5% and 16.4% with our methods respectively compared with the original PSD when using 2 quantization bits, and peak signal to noise ratio (PSNR) of $35.7dB$ and $35.0dB$ is achieved when employing 3 bits for quantization. Moreover, we also propose circuits to implement these algorithms, by shifting voltages at either reset phase or readout phase. Transient simulation results finally validate our methods.

The paper is organized as follows. Section II illustrates the DR loss problem of the PSD algorithm from [5]. Section III presents our proposed blocked PSD and auto-reset PSD with theoretical analysis and quantitative simulation results. Section IV describes the circuit implementation of the proposed PSD algorithms. Section V concludes this work.

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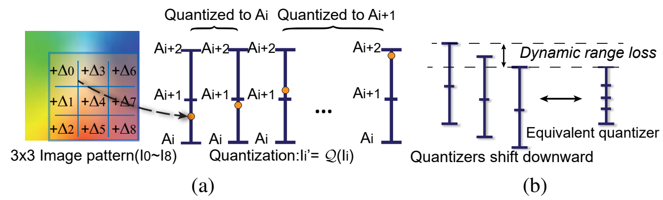


Fig. 1. The PSD algorithm (a) If there are more neighboring pixels quantized to A_{i+1}, then the pixel value in interval $[A_i, A_{i+1}]$ is more closer to A_{i+1} other than A_i. (b) Quantizers shift downward when $\Delta_i > 0$. Multiple coarse quantizers for an image patch is equivalent to a single quantizer with high accuracy. DR loss occurs due to coarse quantization for bright pixels.

II. Analysis of PSD Algorithm

The PSD algorithm assumes a locally constant model for images because adjacent pixels usually exhibit strong correlations (Markov property), and tries to refine estimations by taking neighboring pixels into consideration. Suppose i is the index of the pixel being estimated. The uncertainty range of pixel i and its 8-connected pixels $\mathcal{N}_i$ are represented by $\mathbb{U}_i$ and $\mathbb{U}_{\mathcal{N}_i}$, respectively (uncertainty range here is an interval). Because the image is assumed to be locally uniform, the uncertainty range of pixel i can be reduced as the intersection:

$$\mathbb{V}_i = \bigcap_{\mathbf{j} \in \mathcal{N}_i \bigcup \{i\}} \mathbb{U}_j \tag{1}$$

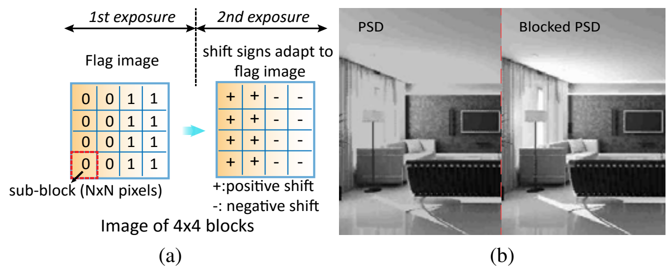


Fig. 2. (a) In blocked PSD, sign of shifts are adapted to the illumination for each sub-block. (b) Reconstruction image using PSD (left) and blocked PSD (right) using just 2 quantization bits.

where the new uncertainty range $\mathbb{V}_i$ is obtained with improved accuracy. If the image patch is uniform ($\mathbb{U}_0 = \mathbb{U}_1 = ... = \mathbb{U}_8$), the new uncertainty range $\mathbb{V}_i$ will not be reduced; whereas if the pixel values in the uniform patch are shifted with predefined values before quantization so that corresponding uncertainty ranges are also shifted ($\mathbb{U}_0 \neq \mathbb{U}_1 \neq ... \neq \mathbb{U}_8$), a finer uncertainty range can be obtained.

Fig. 1 further illustrates the PSD algorithm. The original image is divided into patterns of 3×3 pixels $I_i (i = 0, ..., 8)$ and pixels in each pattern are shifted by different amounts $\Delta_i = (i-1) * \delta$ (δ is a constant). Pixels are then quantized to be $I_i^{'} = \mathcal{Q}(I_i + \Delta_i)$ ($\mathcal{Q}$ is the quantization operator) using a coarse quantizer with quantization levels $A_0, A_1, ..., A_m$ ($m = 2^n - 1$, where n is bit number). These quantized values are used to estimate the true value for the center pixel ($I_4 \triangleq I_{center}$). Suppose I_{center} falls within $[A_k, A_{k+1}]$: if I_{center} is closer to A_k, then the chance that quantized shifted values are above the upper quantization level ($I_i^{'} > A_{k+1}$) is small (the chance will be larger if I_{center} is closer to A_{k+1}). As a result, I_{center} can be determined more accurately.

Essentially, the process of adding positive shifts to the signal is equivalent to moving quantization levels downward. As shown in Fig. 1b, coarse quantizers with quantization levels positioned at different places are equivalent to a single quantizer with high quantization resolution. However, there exists a DR loss because bright pixels cannot be well reconstructed using positive shifts. The DR loss is 23.3% when quantizing 2 bit-depth and 11.5% for 3 bits, which limits its application in wide dynamic range environments.

III. Algorithms for DR Loss Compensation

A. Blocked PSD

As shown in Fig. 1b, positive shifts induce a DR loss in bright pixels and similarly, negative shifts cause a DR loss in dark pixels. Based on this observation, our blocked PSD divides the image into sub-blocks with $N \times N$ pixels, and adjusts sign of shifts ($\Delta_i > 0$ or $\Delta_i < 0$) for each block according to the illumination intensity. During the operation, two images will be captured, as shown in Fig. 2a, where the first captured image will be quantized into a binary image to determine the average illumination level for each sub-block; if there are more pixels to be binary one, $flag = 1$ is specified for that block. Afterwards in the second capturing, corresponding shifts are introduced to sub-blocks based on the flag image (for instance, shift upward with $\Delta_i < 0$ for the sub-block if $flag = 1$).

The block size should be appropriate to avoid blocking artifacts and much transmission overhead. $N = 16$ is a proper block size in our simulation. Fig. 2b shows the simulation result with blocked PSD using 2 quantization bits. The highlight region near the lamp can be well recovered while details will be lost in original PSD due to the dynamic range loss.

B. Auto-reset PSD

In [6], the unwrapping method that is well-studied in MRI is used to provide ultra-high dynamic range imaging. Based on this technique, an auto-reset PSD algorithm is proposed to address the aforementioned DR loss problem. The working principle is similar to pulse frequency modulation (PFM) sensors: the discharging photodiode is reset whenever it drops below a reference voltage. However, there is a fundamental difference that no counters will be employed because the reset counts will be recovered by algorithm only.

After acquisition with auto-reset scheme, the quantized image $I_{i,j}^{\psi}$ is modeled as the modulo of original image $I_{i,j}^{\phi}$:

$$I_{i,j}^{\psi} = mod(I_{i,j}^{\phi}, I_0) \tag{2}$$

where mod is the modulus operator and I_0 is the divisor. The process of recovering true image $I_{i,j}^{\phi} = I_{i,j}^{\psi} + kI_0$ is reduced to finding the optimal wrap counts k. In natural images, neighboring pixels usually appear similar, so we can unwrap the image by minimizing the energy function of first-order Markov Random Field (MRF) formulated as [7]:

$$\begin{aligned} arg \min_{(i,j)\in\mathbb{G}} [&V(I_{i,j}^{\psi} + k_{i,j}I_0, I_{i-1,j}^{\psi} + k_{i-1,j}I_0) \\ &+ V(I_{i,j}^{\psi} + k_{i,j}I_0, I_{i,j-1}^{\psi} + k_{i,j-1}I_0)] \end{aligned} \tag{3}$$

where clique potential V represents how much neighboring pixels interact and $\mathbb{G}$ is the set of pixel locations. In this work we use the PUMA algorithm [7] that minimizes the MRF energy using the maximum-flow graph-cut method.

Fig. 3a shows an original image with grayscale gradient, while Fig. 3b is the image directly quantized with 2 bits, causing false contours that deteriorate image quality. There is noticeable information loss for the brightest region when using PSD (Fig. 3c) while the full dynamic range can be well recovered with our auto-reset PSD as shown in Fig. 3d. In our simulation for a complex indoor environment, Fig. 3e is the modulo image captured from the auto-reset operation, and reconstruction image in Fig. 3f with 2-bit depth shows a satisfying image quality with $PSNR = 34.6916$ and $SSIM = 0.5782$ (SSIM is a better metric for measuring image quality).

C. Experiments and Comparison

We have shown reconstructed images by blocked PSD and auto-reset PSD in Fig. 2b and Fig. 4b. To compare with PSD quantitatively, we evaluate our algorithms on image sets with different quantization bits. Fig. 4 shows image quality results

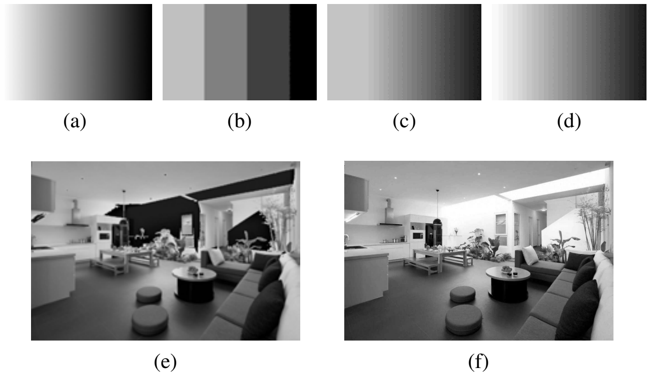


Fig. 3. Simulation result of auto-reset PSD. (a) Original image of gray scales. (b) Image quantized with 2 bits directly. (c) PSD reconstructs image with much improved quality, but there is noticeable DR loss for bright pixels. (d) Image reconstructed by auto-reset PSD is free of DR loss. (e) Modulo image for an indoor environment. (f) Reconstructed scene by auto-reset PSD using 2 bits.

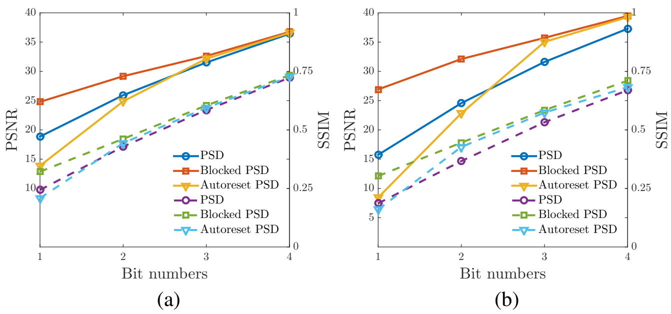


Fig. 4. Simulation results of proposed methods (solid line: PSNR; dot line: SSIM). (a) Test on image of Lichtenstein Castle (b) Test on a real indoor environment (scene in Fig. 3f)

for two images: the Castle of Lichtenstein and an indoor environment. It can be shown that the performance of blocked PSD is always the best, whereas auto-reset PSD outperforms original PSD when using more than 2 bits. When 2 bits are quantized, SSIM values of blocked PSD and auto-reset PSD for the indoor room improve by 21.5% and 16.4% respectively over original PSD, while these numbers improve by 9.7% and 7.7% respectively when using 3 bits. Also, both our algorithms can achieve high PSNR ($35.7dB$ and $35.0dB$) with just 3 bits. In comparison, blocked PSD steadily provides better image quality, whereas auto-reset is more power efficient with a single exposure, and is capable to image scenes with ultra-high dynamic range [6].

IV. Hardware Implementation

A. Implementing PSD Algorithm

In active pixel sensor (APS), the photodiode is first reset, then after integration it is read out with the voltage drop being proportional to illumination intensity. Since there are two phases that can be manipulated, we can introduce shifts for PSD at either the reset phase or the readout phase.

1) Shift at Reset Phase (circuit I): Fig. 5a shows the pixel design in this scheme. Initially, each pixel in a 3×3 pattern is reset (shifted reset) with different voltages ($Vdd - i\Delta V$, $i = 0, 1, ..8$) by turning on M1. After integration, switch S1 is closed for autozeroing of the DDS (difference double sampling) circuit. M4 is then turned on so that the photodiode voltage is sampled by DDS. After that, switch S1 is reopened, the pixel is reset (common reset) to the common voltage Vdd by turning on M2, and pixel voltage is sampled by the DDS again. The output of DDS, which will be quantized by a low resolution ADC, provides the difference of two readouts — the sum of voltage drop due to discharging photocurrent and voltage shift $i\Delta V$ due to different reset voltages (Fig. 5b).

It should be noted that PMOS source followers (M3) for pixels have to be employed in this design because non-unity voltage gain ($A_{SF} < 1$) of NMOS source follower would result in an effective voltage shift lower than expected, which is transferred from shifted pixel supply to column line. Shifted voltages ($Vdd - i\Delta V$) are generated by DACs and buffered to drive pixel array as shifted reset voltages. Buffers in total consume less power because each row of pixels will be driven by three buffers together.

2) Shift at Readout Phase (circuit II): Another scheme for introducing shifts is that the shifts required by PSD can be applied to the reference voltage of the DDS circuit. Typically, the output of DDS equals $V_{REF} - (V_{RST} - V_{SIG})$, where V_{RST} represents the reset voltage and V_{SIG} denotes pixel signal voltage. If we use different reference voltages V_{REF1} and V_{REF2} for double sampling of readout signal and reset signal respectively, the DDS output will be

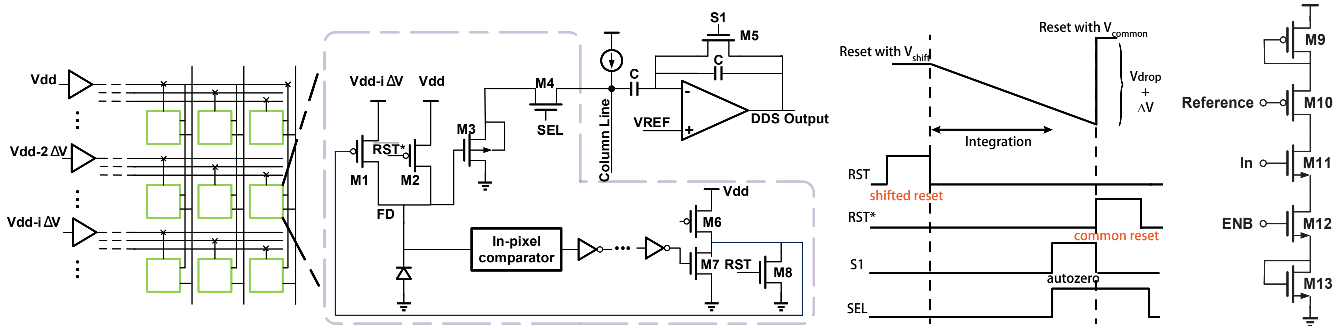
$$V_{OUT} = (2V_{REF1} - V_{REF2}) - (V_{RST} - V_{SIG}) \qquad (4)$$

Therefore, if we choose different reference voltage V_{REF2} for pixels in the 3×3 pattern (V_{REF1} is fixed), the pixel voltage is sensed with proposed shifts. That is, if $V_{REF2} = V_{REF1} + \Delta V$ is used for specific pixel with voltage V_{SIG}, then that pixel will have an equivalent value of $V_{SIG}^{'} = V_{SIG} - \Delta V$, which is shifted as the PSD algorithm expected.

B. Extending Designs towards Algorithms Without DR Loss

We further extend the above hardware designs to implement proposed algorithms that are free of DR loss. For the blocked PSD, firstly a binary image without shifts is obtained: if there are more binary ones in the block i, negative shifts should be used in the second exposure, and vice versa. In order to shift either upward or downward, more reference voltages need to be generated for both circuit I and II. Besides, circuit I should have one more PMOS reset transistor in each pixel to select the additional supply voltage $Vdd + i\Delta V$.

To implement auto-reset PSD, the photodiode is auto-reset using feedback circuit which consists of an in-pixel comparator and a delay unit, as shown in Fig. 5a. Whenever the photodiode voltage V_{FD} drops below the reference voltage, feedback will turn on M1 to reset pixel. This 2-T in-pixel comparator (Fig. 5c) from [8] shares current limiters (M9, M13) and enabler (M12) by column. Inverters chain is employed as a delay unit so that pixels have sufficient time to reset. NMOS transistors M7 and M8 share the common current load M6, and are used to reset the photodiode by



(a) (b) (c)

Fig. 5. (a) Diagram of circuit I with in-pixel comparator for auto-reset. (b) Principal of shifting at reset phase and circuit timing. (c) In-pixel comparator.

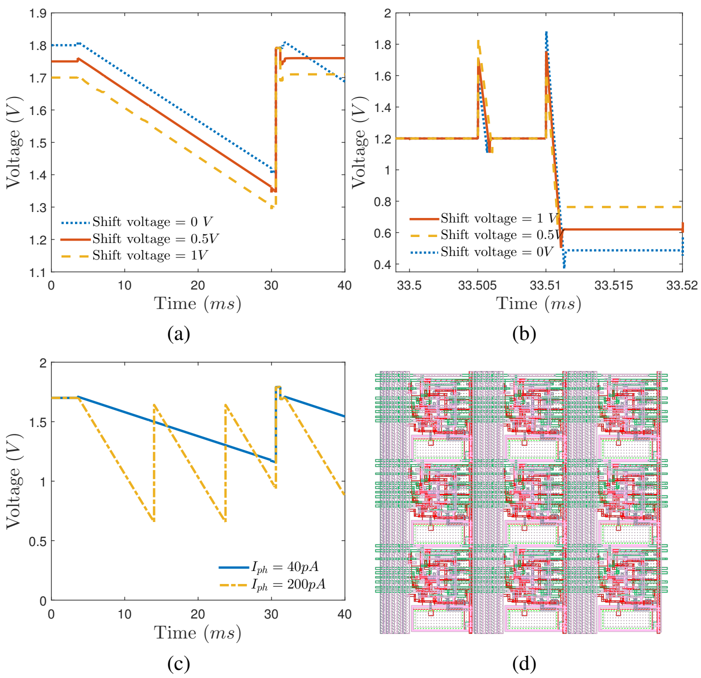


Fig. 6. (a) Shift at reset: there is a shift between two resets. (b) DDS output of circuit I: shifts are $0V$, $0.5V$ and $1V$ respecitively for pixels with the same values (c) Auto-reset (d) Pixel layout for circuit I with auto-reset

internal and global reset control respectively. Different from traditional PFM image sensor that uses counter to count reset numbers, our design employs no storage cell, thus providing a higher fill factor.

C. Simulation result

We will show transient simulations with GlobalFoundries 0.18 um process for justification. Fig. 6a shows the simulation result of photodiode voltage in shifting at reset phase scheme. The difference of readout signal and common reset voltage is calculated by DDS, whose output curve is shown in Fig. 6b. The overshoot in Fig. 6b is due to charge injection in auto-zero and amplification period of DDS operation. Circuit II that uses different V_{REF2} as reference voltages for DDS during amplification has a similar transient result. Fig. 6c shows the plot for pixel voltage drops under different illumination intensity when in auto-reset mode. The pixel layout of a 3×3 pattern for circuit I with auto-reset mode is shown in Fig. 6d and pixel size is $13 \times 15\,\mu m$. Although with a relatively low fill factor, this design is still worthwhile because conversion time can be reduced by 96.9% than 8 bit SS ADCs because 3 bits will be quantized. Also, the power required for data transmission is reduced as well. On the other hand, circuit II may provide a smaller pixel pitch because it uses standard 3T or 4T pixel structure when using blocked PSD, and unlike circuit I, it does not require extra buffers. When employing the auto-reset structure, circuit II can provide ultra-high dynamic range with modest increase in pixel size.

V. Conclusion

In this paper, we proposed two algorithms that address the DR loss issue of the PSD algorithm. We also proposed two circuit schemes that can implement PSD and they are also compatible to our proposed algorithms. The methods presented in this paper are promising because they allow a simultaneous reduction of power from ADC and transmission. Future work would involve testing the sensor and possibly combining these ideas with other compression methods in order to further improve compression.

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