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DSR-QBD: A Multi-Frame Approach for Disparity-Robust Reconstruction in 2×2 OCL Quad-Bayer Sensors

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Abstract

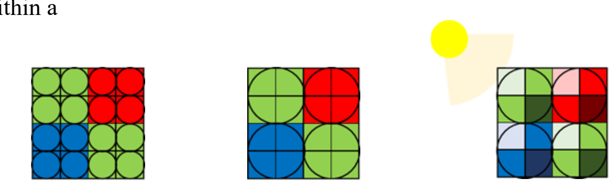
In this paper, we propose the DSR-QBD framework, which integrates Deep Burst Super-Resolution (DBSR) with U-Net-based 2x2 OCL Quad-Bayer Demosaic. Traditional single-frame methods often struggle with the inherent disparity issues present in 2×2 On-Chip Lens (OCL) Quad-Bayer sensors. Our proposed framework addresses these challenges by treating a single 2×2 OCL image as multiple phase-separated frames, enabling the application of advanced multi-frame super-resolution techniques. Unlike conventional single-frame approaches, our method addresses the disparity issue in 2×2 OCL Quad-Bayer sensors by treating a single 2×2 OCL image as multiple phase-separated frames and applying multi-frame techniques. This strategy enables the effective utilization of phase images to enhance reconstruction quality. Furthermore, the integration of U-QBD within DSR-QBD mitigates the limitations of DBSR, particularly in correcting false pattern artifacts that may arise during reconstruction, thereby yielding more stable and natural results.

INTRODUCTION

Recent advancement in sensor technology have driven the development of smaller pixel sizes and higher pixel densities, enabling the capture of increasingly detailed and sharp images. However, this trend comes with a significant trade-off: reduced sensitivity in low-light conditions. As pixel sizes shrink, the amount of light captured by each pixel decreases, leading to challenges in maintaining image quality, especially in dimly lit environments. This limitation has become a critical bottleneck in the pursuit of enhanced camera performance. To address this challenge, the 2x2 Quad Bayer structure was introduced as an innovative solution. In this design, pixels of the same color are grouped into 2x2 blocks, allowing the sensor to operate in two distinct modes: high-resolution mode and low-light mode. In high-resolution mode, each individual pixel is used to capture fine details, while in low-light mode, the 2x2 block of pixels is treated as a single larger pixel, effectively increasingly sensitivity and improving image quality under poor lighting conditions [1]. Effectively exploiting such sensor architectures, however, requires sophisticated image restoration methods. Among the fundamental techniques for achieving high-quality imagery in the field of digital image processing are Demosaicing and Super-Resolution.

In addition, 2x2 On-Chip Lens (OCL) sensors have been widely adapted, utilizing the inherent optical disparity among four pixels in a 2x2 block to enable autofocus[2, 3]. However, 2x2 OCL sensors have inherent limitations when demosaicing, occurring visual artifacts under specific conditions.

Meanwhile, Multi-Frame Super-Resolution (MFSR) [4, 5] has attracted considerable attention, as it leverages complementary information embedded across multiple low-resolution images of the same scene. In contrast to Single-Image Super-Resolution (SISR)[6], which relies solely on the spatial information contained within a single image, MFSR exploits temporal redundancy and inter-frame variations to restore finer details. By aligning and fusing multiple frames, MFSR achieves higher image quality and greater robustness to noise, thereby surpassing the capabilities of single-image approaches.



(a) (b) (c)

Figure 1: (a) and (b) are representing 1x1 and 2x2 On-chip Lens (OCL) Quad-Bayer sensor, respectively. (c) illustrates the phase-dependent disparity in 2x2 OCL Quad-Bayer sensor under strong oblique illumination

In this paper, we propose a novel demosaicing method specifically tailored for the 2x2 OCL Quad-Bayer pattern. Our approach involves the separation of each phase component to generate pseudo-burst images, which are then processed using Deep-Burst Super-Resolution (DBSR) techniques[5]. By treating these pseudo-burst images as burst sequences, our method achieves the production of demosaiced images with significantly enhanced quality and detail.

The contribution of this paper are outlined as follows:

1. DSR-QBD framework: We propose a novel framework that integrateds DBSR with U-Net-based reconstruction method tailored to 2x2 OCL Quad-Bayer sensors while overcoming the limitations of single-frame approaches.
2. Multi-frame perspective: A single 2x2 OCL image is decomposed into phase-separated views and treated as multiple frames., effectively exploiting phase disparities for improved reconstruction.
3. Enhanced restoration: The proposed method alleviates disparity artifacts in edge and high frequency regions, while the complementary integration of DBSR and U-Net-based Quad-Bayer Demosaic (U-QBD) ensures more stable and natural restoration.

DEMOSAIC IN 2X2 OCL QUAD-BAYER

The Quad-Bayer pattern is widely utilized in camera image sensors, representing a prevalent technology in modern imaging systems. As illustrated in Fig. 1, the Quad-Bayer structure can incorporate both 1x1 and 2x2 OCL configurations, which showcases its versatility in sensor design. Among these, the 2x2 OCL technology has gained significant popularity due to its ability to implement autofocus (AF) across all pixels without the need for dedicated AF pixels. This innovation enhances both functionality and efficiency in image sensor design. However, due to the sharing of OCLs with adjacent pixels, the 2x2 OCL configuration exhibits a disparity phenomenon,

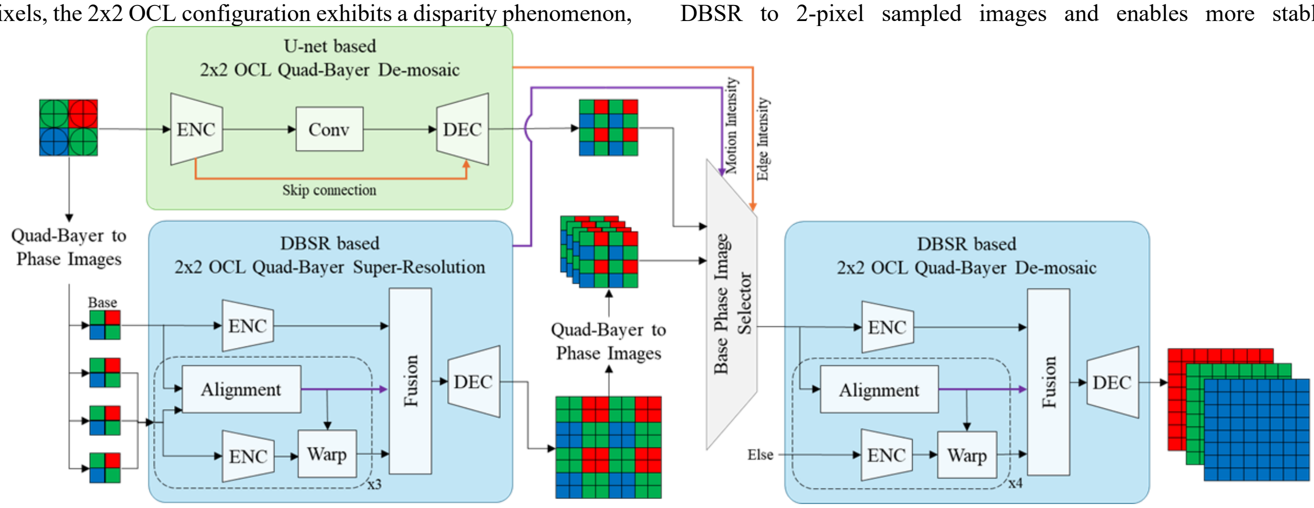


Figure 2: Flow diagram of the DSR-QBD framework. The method leverages multi-frame inputs sampled from a 2×2 OCL Quad-Bayer array, combining DBSR and U-QBD to address disparity and enhance image quality.

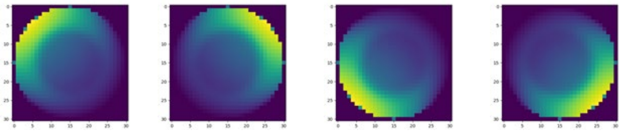
unlike the 1x1 configuration, which complicates the demosaicing process significantly. Therefore, specialized demosaicing techniques tailored to the characteristics of 2x2 OCL sensors are required. In this context, phase-distinct images of 2x2 OCL sensor can be interpreted as independent images across different phases, providing four distinct views. Building on this insight, the present study applies deep learning-based MFSR to 2x2 OCL Quad-Bayer sensor. Although no explicit temporal information is available, disparity regions induced by optical factors behave as if motion were present, making a multi-frame-based approach particularly well suited. To further enhance reconstruction quality, we propose a novel network that integrates MFSR with a dedicated 2x2 OCL Quad-Bayer demosacing technique, thereby addressing the limitations of each method and improving overall performance.

PROPOSED METHOD

In this study, we aim to enhance the demosaicing performance of 2x2 OCL Quad-Bayer sensors by leveraging prior research on DBSR, which has shown remarkable effectiveness in exploiting motion information from consecutively captured burst frames. Instead of burst images, we apply DBSR to 2x2 OCL Quad-Bayer data by obtaining via 2-pixel interval sampling, as if they were captured from independent Bayer sensors. This approach is motivated by the fact that 2x2 OCL sensors exhibit substantial phase disparities, allowing each phase image to be regarded as a separate input. Under well-focused conditions, motion among down-sampled Bayer images is negligible; however, defocus or strong oblique lighting induces sub-pixel disparities. In addition, the 2-pixel interval down-sampling process may introduce aliasing artifacts, leading to image degradation, particularly in high-frequency spatial regions and along edges. Our proposed algorithm is designed to address the primary challenges while simultaneously alleviating the additional issues that may emerge as a consequence, thereby improving performance and accuracy. In this work, we integrate U-Net-based 2x2 OCL Quad-Bayer Demosaicing (U-QBD) [7, 8], a technique that employs a U-Net architecture to transform a 2x2 OCL Quad-Bayer structure into a standard Bayer pattern. Although U-QBD tends to introduce some blurring while reducing disparity, it effectively restores images by leveraging adjacent information. As a result, U-QBD provides richer spatial information than applying DBSR to 2-pixel sampled images and enables more stable reconstructions in regions prone to aliasing artifacts or dominated by edges.

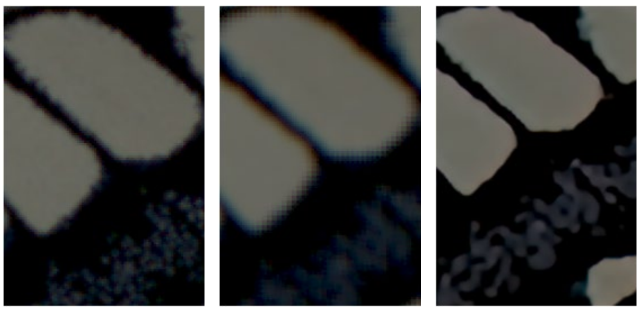
Accordingly, we introduce the DSR-QBD framework, which integrates U-QBD with DBSR to overcome aliasing artifacts and false-color distortions induced by sampling. As shown in Fig. 2, the framework operates in two stages. First, in the case of a single 2x2 OCL Quad-Bayer image, four distinct 1x1 Bayer images are sampled and generated, corresponding to the four phases, as depicted in Fig. 2. These four images collectively serve as the input for the DBSR framework. Four 1x1 Bayer images are then utilized by the DBSR algorithm to perform advanced computations, including optical flow estimation, precise alignment, and spatially adaptive fusion, ultimately producing high-quality demosaiced outputs. This methodology underscores the effectiveness of leveraging phase-specific data to overcome the inherent challenges of 2x2 OCL Quad-Bayer imaging, thereby advancing the field of computational photography. DBSR improves reconstruction quality by calculating the optical flow between a base phase image and the remaining three phase images, aligning them precisely, and subsequently merging the results through spatially adaptive weighting. During the fusion process, edge regions receive greater weight from the base phase image to preserve structural details, while flat regions leverage contributions from the other phase images for noise suppression. This approach ensures enhanced detail preservation and overall image fidelity. The first DBSR stage performs 4x super-resolution, ensuring resolution consistency when combined with U-QBD.

In the second DBSR stage, the first output is down-sampled to match the size of the U-QBD output. To optimize the reconstruction process, our framework incorporates a Base Phase Image Selector [9] which plays a pivotal role in determining the most suitable base image for subsequent stages. This selector evaluates the presence of high-frequency components within the images and decides whether to utilize the output from the U-QBD stage or one of the DBSR inputs as the base image. This intelligent selection mechanism is designed to minimize potential quality degradation that may arise when relying solely on DBSR. By dynamically choosing the optimal base image based on the content characteristics, our approach



(a) (b) (c) (d)

Figure 3: Point Spread Function (PSF) kernels applied to make 2x2 OCL Quad-Bayer sensor image. (a)-(d) correspond to four different phases, each representing the distinct optical response to the sensor for phase-separated inputs.



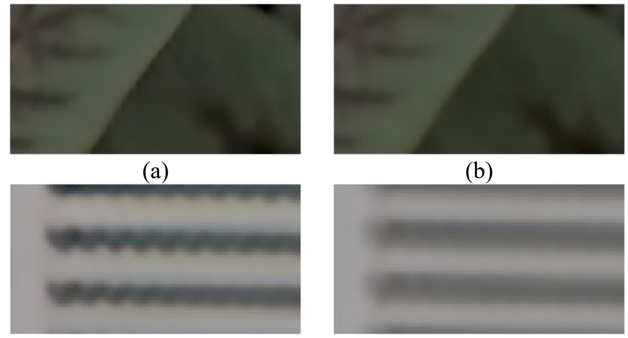
(a) (b) (c)

Figure 4: Comparison of disparity effects and reconstruction results. (a) Reconstructed Quad-Bayer image, where no significant disparity is observed at edges. (b) Result of 2×2 OCL modeling, in which edge regions exhibit phase-dependent splitting and misalignment. (c) Reconstruction using the proposed DBSR on 2×2 OCL Quad-Bayer input, where disparity artifacts are effectively mitigated and resolution is further enhanced by adjusting the scaling factor.

ensures that the reconstruction process remains robust and adaptable to varying image conditions. Consequently, this strategy leads to more stable and consistent reconstruction performance, significantly enhancing the overall quality of the final output. By leveraging advanced decision-making processes through the Base Phase Image Selector, we achieve a balanced and efficient solution that not only mitigates artifacts but also preserves intricate details and textures, setting a new standard for demosaicing techniques in computational imaging.

RESULTS

In this study, the PixelShift200 dataset was employed [10]. To evaluate the demosaicing performance of the 2x2 OCL Quad-Bayer sensor, we applied distinct point spread function (PSF) kernels to each phase of the PixelShift200 images (Fig. 3) thereby generating synthetic raw data closely resembling the captured by an actual 2x2 OCL Quad-Bayer sensor [11]. This process effectively simulates the phase disparities originating from the physical structure of the sensor, thereby enabling a rigorous validation of the proposed method. As illustrated in Fig. 4, Bayer sensors demonstrate minimal to negligible phase disparity in regions characterized by edge structures, thereby ensuring coherent spatial alignment and better robustness to edges during image reconstruction. In contrast, applying 2x2 OCL Quad-Bayer sensor modeling to the same scene produces clear separation of edge positions across phases, where edges appear split and misaligned. This phenomenon can be regarded as a fundamental issue inherent to the 2x2 OCL Quad-Bayer sensor architecture. Fig. 5 illustrates how the proposed DSR-QBD framework provides improved results in edge regions.



(a) (b) (c) (d)

Figure 5: Reconstruction improvements achieved by the proposed DSR-QBD framework. (a), (b): Edge regions, where DSR-QBD alleviates the artifacts that typically occur with DBSR alone. (c), (d): Spatially high-frequency regions, where the U-QBD component introduces some degree of blur but still provides more natural and reliable restoration compared to DBSR alone.

DBSR alone effectively leverages the advantages of a multi-frame approach to enhance sub-pixel information and suppress noise, making it highly effective for general scenes. However, in this study, each phase image sampled at 2-pixel intervals from a 2x2 OCL Quad-Bayer sensor is treated as a sub-pixel input to DBSR, which exposes its limitations in edge regions and areas with high spatial frequencies. Specifically, DBSR may introduce false-color artifacts or generate outputs misaligned with the underlying structures due to incorrect directional correction, thereby undermining the naturalness and reliability of the reconstructed images. In contrast, while U-QBD may produce slightly blurred outputs due to its tendency to suppress disparities, the proposed DSR-QBD framework combines it with the multi-frame reconstruction approach to retain the strengths of that method while alleviating its weaknesses in edge and high-frequency regions. As a result, the framework delivers reconstructions that are more stable and perceptually natural.

CONCLUSION

In this paper, we propose the DSR-QBD framework, which integrates DBSR with U-QBD. Unlike conventional approaches that rely on continuously captured burst images, the proposed method employs phase images sampled at two-pixel intervals from a 2x2 OCL Quad-Bayer array as inputs to DBSR. In this process, sampling artifacts may occur, particularly in periodic patterns and edge components, but these are effectively mitigated through U-QBD. Furthermore, since disparity removal is critical in 2x2 OCL structures, experimental results demonstrate that U-QBD, despite introducing slight blurring, is effective in compensating for pattern artifacts falsely reconstructed by DBSR.

The proposed framework does not merely circumvent the inherent optical limitations of sensor structures but rather leverages the strengths of multi-frame techniques to effectively alleviate them. These findings demonstrate that challenges difficult to resolve with single-frame approaches can be addressed from a new perspective, thereby underscoring the effectiveness of multi-frame methods in enhancing reconstruction quality. Moreover, this study highlights the value of integrating sensor architectures with learning-based techniques, presenting a promising direction for achieving

substantial improvements in image quality. In addition, the proposed approach has the potential to be extended beyond the 2x2 structure to more general NxN Bayer configurations. The base phase image selector, designed in this work with a focus on high-frequency regions, could also be adapted by refining its selection criteria for different objectives. Through such optimization, the framework can deliver more precise and stable improvements in image quality, tailored to specific enhancement goals.
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If you use Microsoft Word's tools for tagging references, please use IEEE style and then format the style tag "-IS&T 11. Reference Created using Word Automation." If you create your reference list manually, use the style "IS&T 11a. References – Manually Created." The latter is a modified version of a numbered list. The end result should look like the sample below.

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