SMARTPHONE-BASED OPTICAL CAMERA COMMUNICATION: CHALLENGES, ADVANCES, AND FUTURE DIRECTIONS⋆

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ABSTRACT

Optical camera communication (OCC) is considered as a key enabler of optical wireless com munication technology. In OCC, light-emitting diodes (LEDs) serve as the transmitter and rolling shutter (RS) cameras as the receiver for high-speed communication. However, the received luminance from the LED is critically important for reliable data retrieval in OCC, which faces challenges due to the inherent nature of data collection. Smartphones, typically equipped with RS cameras, represent one of the most promising platforms for the commercial deployment of OCC. To ensure system reliability, various methods have been proposed to address the diversity in pixel illumination values captured by smartphone cameras. Furthermore, AI-based approaches that make RS cameras compatible with low-speed mobile scenarios and enhance overall system performance also introduce additional system complexity. In this paper, we provide a systematic review of the state-of-the-art methods for data retrieval in smartphone camera-based OCC. In particular, we provide specific challenges due to important factors, such as communication distance variation and the blooming effect. Furthermore, we discuss recent advancements, especially promising AI applications in OCC. Finally, we outline open research directions on smartphone camera-based OCC.

KEYWORDS

Optical camera communication (OCC), rolling shutter camera, smartphone-based OCC, bloom-ing effect.

1. INTRODUCTION

The ever-increasing demand for mobile data has inspired researchers to focus on license free optical spectrum (350 nm-1550 nm) due to its various desirable properties, such as unregulated spectrum, energy efficiency, and high security. In recent times,

David C. Wyld et al. (Eds): WiMNeT, NLDM, EDUPT, SIP, AISO – 2026
pp. 01-10, 2026. CS & IT - CSCP 2026 DOI: 10.5121/csit.2026.1601001

optical wireless communication (OWC), such as visible light communication (VLC) has attracted inten sive interest. OCC, a subject of VLC, is a unidirectional communication technology that broadcasts data using light-emitting diode (LED) transmitters and camera receivers. The wide use of LEDs and cameras, including smartphone cameras, surveillance cameras, and vehicle cameras, enhances OCC's potential. It has attracted significant attention for applications in indoor communication and localization, the internet of things, and intelligent transport systems. Cost-effectiveness and the complete immunity to electromagnetic in terference, due to the spatial separation capability of the camera, are among the most remarkable features of this technology [1].

The rapid advancement of autonomous systems has intensified the demand for reliable optical communication channels that are robust to radio-frequency interference. Camera sensors based on smartphone-grade CMOS technology, already integrated into modern platforms and mobile systems, offer a practical foundation for deploying OCC in real world scenarios where traditional wireless communication may face limitations. In OCC, devices such as Arduino, Analog Discovery, or other controllers can be used in conjunction with an LED driver to operate high-power LEDs. The modulated light emitted from the

⋆ This work was supported by the Fundamental Research Funds for the Central Universities and the Youth Teacher International Exchange & Growth Program under Grant QNXM20250018.

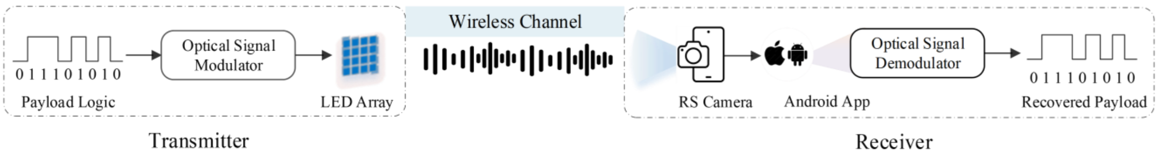

Fig.1. Schematic representation of the smartphone-based optical camera communication system.

LED transmitter passes through the wireless channel and is then received with a global shutter (GS) or rolling shutter (RS) camera depending on the specific application. The transmitted bits are retrieved from the captured luminance value in the image which is illustrated in Fig. 1. GS cameras capture all pixel values simultaneously, which provides a clear LED state on the image sensor, either a dark spot when the LED is OFF or a bright spot when the LED is ON, and typically yield at most one bit per LED state per frame.

To address this low data rate issue, RS cameras are employed as a cost-effective solution to achieve a data rate higher than the frame rate of the camera. It captures the light sequentially, either horizontally or vertically, which is reflected as either a bright or a dark stripes, respectively, depending on the LED ON and OFF states. Multiple bright and dark stripes are captured in a single image frame corresponding to the LED blinking pattern resulting in a data rate higher than the frame rate. However, continuous data transmission is not feasible with RS cameras due to the readout time required between consecutive image frames. Therefore, data are transmitted in the form of packets, and each packet is transmitted at least twice to ensure reliability. Each data packet begins with a frame header, typically a longer bright pulse than the data-carrying pulses, so it can be easily distinguished. The start of a new frame header indicates the termination of the previous packet, and the data between two consecutive headers are decoded. In this way, even if one packet is corrupted due to overlap with the inter-frame gap, its duplicate remains intact. It is also noteworthy that the lower transmission frequency limit is approximately 100 Hz, to avoid perceptible flicker to the human eye, while the upper limit is constrained by the camera cutoff frequency, above which the flickering pattern can no longer be captured [2].

Smartphones are considered one of the most promising receiver platforms for the fu ture deployment of OCC systems, owing to their widespread adoption, built-in cameras, and computational capabilities [3]. Typically, Android-based smartphones are equipped with low-frame-rate (30–60 frames per second, fps) RS-based cameras due to their cost effectiveness. Despite their potential for supporting high-speed OCC, smartphone-based systems still face several challenges. In this paper, we review the key challenges associ ated with smartphone-based OCC systems, including data retrieval techniques, region-of interest (RoI) detection, and AI-assisted performance enhancement. In particular, we high light issues arising from communication distance variation caused by mobility and analyze how recent advancements, especially AI-driven methods, are addressing these challenges. Finally, we outline open research directions to advance the development of smartphone camera-based OCC.

2 CHALLENGES IN SIGNAL RECEPTION

In a typical RS-OCC system, the light source is generally placed at the center of the image. The light intensity of the LED is highest at the center and gradually diminishes toward the edges. As a result, the captured image exhibits significant spatial variation in light intensity. Consequently, different regions of the image may require different threshold values [4]. In addition, the stripe width varies with transmitter frequency. Stripe width reduces with the increase in transmitter frequency because the receiver has less time to

Fig.2. Testbed demonstration of the blooming effect in smartphone-based OCC.

capture the LED state as either bright or dark. It should also be noted that even for the same transmitter operating at a fixed frequency, the captured stripe width can differ across cameras due to variations in their readout times. For example, at a transmission frequency of 250 Hz, the stripe widths captured by iPhone 5c, iPhone 5s, and iPhone 6 Plus were 108 pixels, 168 pixels, and 158 pixels, respectively. The exposure time was set to 14.73 to minimize background noise, while the readout durations of these devices ranged from 19 µs to 25.5 µs. The achieved throughput was 12 bytes per second, and the overall processing time of each 1920 × 1080 frame on an Apple iPhone 5s was 18.15 ms [3].

Another major challenge in smartphone-based OCC is that the charge of a pixel can saturate by the high intensity of light and overflow to the neighboring pixels, which is known as the blooming effect. Since the blooming effect reduces the contrast between the bright and dark stripes, it can lead to significant errors in header detection, especially in images with high blooming effects. In addition, the environmental condition also influences pixel intensity values. To demonstrate the blooming effect, we developed a testbed as shown in Fig. 2. A Cree XLamp XR-E LED was used as the transmitter, and a Samsung Galaxy A56 smartphone camera was used as the receiver at a distance of 0.5 m. Sample images of the blooming effect are shown in Fig. 3 at two different frequencies (1 kHz and 2 kHz). The LED was driven by an Arduino Nano with an LED driver, while the camera exposure time and ISO were set to 1/6000 s and 3200, respectively. In Fig. 3(a), the expansion of the frame header highlights the difficulty of precisely detecting the header position under blooming, whereas Fig. 3(b) illustrates the risk of dark data-carrying stripes being misclassified as bright stripes due to severe blooming.

It is observed that camera sensors in mobile devices may exhibit blooming artifacts when capturing intense light sources. The authors of [5] observed this issue with a Sam sung GT-S7500 mobile-phone and proposed converting the captured video to 480 × 640 grayscale images and selecting the pixel values of a column matrix of the resulting image, specifically targeting at the regions just outside the center of the blooming effect to ad dress this issue. This ensures distinguishable grayscale values even under a high blooming effect. Consecutive 60-pixel rows of a specific column were organized into groups. These groups are created for all pixel rows to mitigate the blooming effect. Subsequently, a second-order polynomial is constructed as a threshold indicator using these pixel values

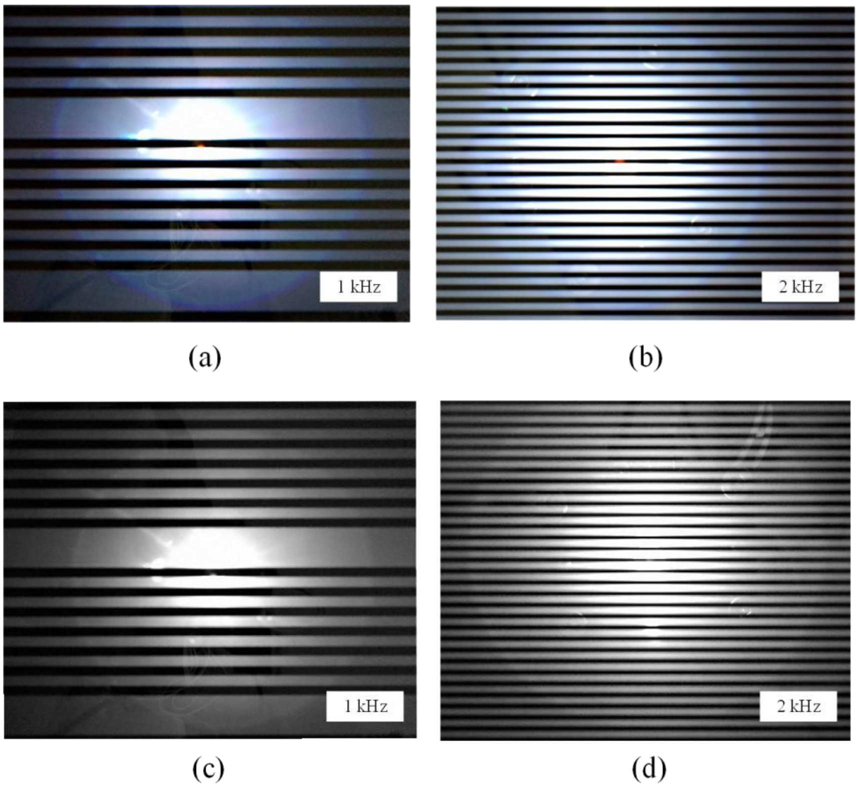

Fig.3. Illustration of the blooming effect captured by a Samsung A56 camera at different frequencies: (a) and (b) original images, and (c) and (d) processed images.

to facilitate the data extraction process. The literature has also explored higher-order polynomial fitting-based thresholding for noisier data patterns in [6]. Initially, the bloom ing effect and background noise are addressed through second-order polynomial fitting. Subsequently, histogram equalization is applied to enhance the extinction ratio (ER) of bright and dark fringes, where ER represents the power ratio of the ON state to the OFF state. A higher ER indicates higher contrast which is essential for reliable data extraction, particularly in binary modulation schemes. It is noteworthy that ER can be influenced by several factors, such as the quality of optical components, modulation schemes and their parameters, and environmental conditions. The resulting image is further processed with a Sobel filter to emphasize edges. Finally, the threshold is determined with a third-order polynomial.

However, these methods are exclusively applicable to centrally positioned light sources. When the LED is moved towards the edges, a major part of the image is dark, delivering a zero grayscale value after processing a bright stripe. To address this issue, the impact of variations in the light source position was studied by adjusting the LED horizontally and vertically in [7]. The region-growing algorithm was employed to track the light source, determining a suitable threshold value from the image histogram to distinguish the LED from the background. Then, starting from the LED's center, the desired area to the left and right side of the LED is selected to avoid zero grayscale pixel values of the image. A single column of the resulting image was then extracted and smoothed using a second order polynomial fitting to facilitate data decoding. To minimize pixel value fluctuations, clipping was applied to any values exceeding the approximated second-order polynomial value. Finally, quick adaptive (QA) thresholding is used for data extraction. The system's BER performance was found to be independent of the horizontal movement of the LED along the center of the image frame.

Conversely, attempts have been made to modify the existing methods for particular applications as the second-order and third-order polynomial scheme is susceptible to fast changing high dynamic contrast images. Even the QA scheme that considers the weighted moving average in the prior direction of the RS pattern faces challenges at high illumina tion conditions. To mitigate this problem, the weighted moving average is considered in both directions in modified QA. Blooming effect mitigation, linear interpolation, and ER enhancements are performed as data pre-processing steps before thresholding. The BER performance improvement is achieved at the cost of an increase in the processing time. Although the proposed scheme works satisfactorily when the LED is located at the center of the image, the ER enhancement scheme may not be suitable for images capturing part of the LED light source [8].

In addition to the aforementioned issues, several factors can influence the reliability and performance of smartphone camera-based OCC systems. In practical environments, vari ations in ambient illumination may significantly affect the captured optical patterns and disrupt the decoding process. Changes in lighting conditions can reduce symbol contrast or introduce background noise, which can significantly degrade the data decoding accu racy. In the literature, learning-based techniques have been explored to improve symbol classification under varying lighting conditions [9]. However, despite these improvements, practical deployments may still experience issues such as misclassification between visually similar codes or reduced accuracy when the captured images have low spatial resolution.

Another limitation arises from the characteristics of commodity smartphone cameras. Their relatively low frame rates can introduce flicker and temporal artifacts during sig nal acquisition, which can restrict achievable data rates. Motion-related effects, such as motion blur caused by camera movement, may further distort captured signal patterns and increase decoding errors [12] [13]. Interference from surrounding LED sources or other lighting infrastructure can also result in unstable reception in dynamic environments. Al though signal processing and learning-based techniques have been proposed to mitigate these effects, they may introduce additional processing overhead or may not scale efficiently for real-time implementations on mobile devices.

System-level factors also contribute to performance limitations in OCC systems. Mis matches between the transmitting display and the receiving camera can complicate accu rate RoI detection and synchronization. To address this issue, detection frameworks based on machine learning have been investigated in the literature [11]. Nevertheless, such ap proaches may require high-refresh-rate displays or impose additional computational com plexity on resource-constrained smartphones. Similarly, insufficient channel characteriza tion may limit the accurate modeling of the optical link, potentially leading to performance degradation at larger distances or under variations in viewing angles [10].

Table 1. Review of smartphone camera-based OCC

Ref.	Challenge addressed	Solution approach	Application	Remaining challenges
[9]	Ambient light Disrupting decoding.	CNN to classify LED Code pattern sunder Varied lighting.	Indoor positioning; robustdecoding despitelight variation.	Misclassification Between similar codes; low-resolution input.
[10]	Lack of channel characterization.	Experimental beam profile, Lambertian order, power under tilt/rotation.	S2Cdemowith smartphones.	Performancedrops beyondsmall distance;limited throughput;frame delays.
[11]	Camera–display mismatch,poorRoI detection.	YOLOforRoI;CNNs forsymboldecoding andsynchronization.	ImperceptibleD2C (ads,signage, subtitles).	Lowdatarate;needs high-refreshdisplays; ambient sensitivity; CNNcostondevices.
[12]	Lowfps,flicker, motionartifacts.	Self-synchronizing ON/OFFOCC; flicker-free.	Stableindoor localizationand decodingwith30fps cameras.	Limitedthroughput; notsuitedforhigh dataratesorbright outdooruse.
[13]	Motionblur,LED interference,unstable reception.	C- OKmodulation; NNforLED detection;neural deconvolutionfor blur.	IndustrialIoT: temperature monitoringviaOCC tocloud.	Verylowrate; BER Rises with distance/blur;NN processingoverhead; scalingissues.
[14]	Signaldistortion, blooming,noise,low throughput.	DCO-OFDMwith DSPalgorithms (P-CVS,D-ELFC, downsampling).	Testbedwith smartphone;achieved improvedOCCrate.	Stillfps-limited;BER sensitiveto light/distance;DSP complexity;scalability issues.
[15]	Lowframerate, flicker,shortrange, mobilitylimits.	Rolling-shutter decoding(OpenCV).	AndroidOCCdemo.	Lowdatarate; limitedmobility;LED sizedependence; energyandprocessing inefficiency.
[16]	Limited camera bandwidth.	Dual modulation Using colorandmono	Higher through put viadual-camera	Camera tuning; cameraasynchrony.

	cameras.	Reception (with post-ynchronization).

3 EMERGING TRENDS AND FUTURE DIRECTIONS

3.1 Mobility Support for Rolling Shutter Cameras

The commercial RS camera receivers experience severe image deformation in mobile sce narios, leaving GS cameras the only option for a high mobility environment. The conse quences of mobility in RS receivers can be two-fold: one is the blurriness created in the image, and the other is the deformation of the stripe pattern. Recently, artificial intelli gence (AI)-empowered OCC systems have been introduced to tackle the challenges created by the walking speed (2 m/s) movement of the RS-camera receiver. In addition, as OCC is a unidirectional and asynchronous communication system, the precise detection of the frame header is essential. This precision is necessary because the pixel values adjacent to the header are crucial for extracting the transmitted data. Recently, the YOLOv5 algo rithm has been employed to detect the starting position of frames in both On-Off Keying and Orthogonal Frequency-Division Multiplexing (OFDM) schemes, thereby enhancing the reliability of OCC systems [17] [18].

In addition, mobility support requires LED detection and tracking, which imposes additional computational burden on the system. The authors of [15] reported that, for a 20 fps camera, an extra 20 ms of processing time per frame was needed to detect and track LEDs within each image. Moreover, the presence of multiple transmitters in a single captured frame introduces further processing overhead. Using FSOOK modulation at 2 kHz and 4 kHz, a maximum communication distance of 7.5 m was achieved with Google Pixel 2 and Galaxy S7 Edge smartphones, where the camera exposure time was set to 1/8000 s and Android Studio API Level 26 was used. The processing time was recorded 45 ms per frame. Furthermore, to achieve higher data rates and enable multi-transmitter tracking, [19] proposed a YOLOv11n-based model incorporating feature re-identification and an extended Kalman filter for an OFDM-based system supporting mobility up to 4 km/h. The system was implemented at a communication distance of 4 m and achieved 4.16 kbps per LED with a BER of 10−4 using an OFDM scheme in a dual-LED environment. Therefore, it is anticipated that more advanced AI algorithms can be applied for further improving OCC systems performance under mobile conditions.

3.2. Promising AI-Based Solutions

Since precise data decoding strongly depends on the captured non-linear luminance values within stripe patterns, AI techniques have been introduced to enhance the reliability of OCC systems. For example, [20] employed U-Net to accurately classify stripe patterns under extremely low-light conditions, where the pixel intensity histograms of bright and dark stripes significantly overlap. This method simplifies data extraction by binarizing the entire image, thereby eliminating the spatial and temporal variations of RS cameras. As a result, any column of the binarized image can be selected for data decoding using only an averaging operation. In addition, U-Net has also proven effective in non-line-of-sight (NLoS) OCC scenarios involving light reflections from rough surfaces [21]. Moreover, the challenges associated with partially obscured stripes in NLoS OCC systems have been addressed in [22], where the authors reconstructed the obscured portions of the stripes using a deep neural network and a Generative Adversarial Network was employed to improve the BER.

However, these methods require a significant amount of computational resources, and their long processing time restricts them to offline applications. To address this limitation, several approaches have been proposed, including parameter reduction through quantiza tion and filter pruning, adjusting model depth and parameters, and parallel processing technique, to reduce the processing time and resource requirement to implement them on edge devices [23][24][25]. For instance, quantization reduces the precision of network weights and activations by converting 32-bit floating-point values into lower-precision for mats (e.g., fixed-point or low bit-width representations), while filter pruning improves efficiency by removing redundant or less significant filters in convolutional layers, thereby minimizing resource requirements and inference time. In [23], the authors introduced a parallel quantization-pruning technique to reduce weight storage requirements. In this ap proach, logarithmic quantization was applied to all weights, while biases and activations were linearly quantized. Subsequently, filter pruning was employed, which involves iden tifying and removing redundant or less important filters in convolutional layers, further reducing the number of operations required during inference. In their study, the number of parameters in the optimized U-Net was reduced from 31 million to 3.1 million compared to the original U-Net. These optimizations demonstrate the potential of deep learning-based systems for real-time implementation within cameras, even on cost-effective edge devices. Future research is expected to introduce more advanced AI algorithms to further enhance the performance of OCC systems

3.3 Open Research Directions

The generalized application of smartphone-based OCC systems requires effective mobility support. However, the current capability of RS-OCC under mobility is limited to around 2 m/s, even with the assistance of AI algorithms. While AI algorithms demonstrate great potential in improving system robustness, their real-time deployment on Android smart phones remains an open research challenge. In particular, RoI detection and performance enhancement often require the simultaneous operation of multiple AI models, which further complicates real-time implementation under limited computational resources. Addressing these issues represents an important research direction toward realizing practical, large scale deployment of smartphone-based OCC systems in future IoT and 6G applications. It is note worthy that in OCC research, it is a common practice to use commercial low frame-rate cameras (30–60 fps) to capture images, which are subsequently processed on a computer for detailed performance evaluation. With such frame rates, real-time imple mentation is feasible, as approximately 17 to 33.5 ms are available to process each frame. This time frame is promising for real-time implementation on modern processors.

4 CONCLUSION

The widespread adoption of smartphones offers significant potential for deploying OCC in everyday life. This paper reviewed the systematic challenges in data retrieval, RoI detec tion, and AI-assisted performance enhancement for smartphone-based OCC systems, con sidering both static and mobile scenarios. In addition, we discussed how mobility-induced communication distance variation and blooming effects further complicates reliable decod ing. We also highlighted recent advancements that attempt to mitigate these issues and remaining challenges. Finally, we outlined promising future research directions that can enhance the robustness, scalability, and real-world applicability of OCC systems across diverse smartphone platforms and usage contexts.

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