RayTrack: Enabling Interference-Free Outdoor Mobile VLC with Dynamic Field-of-View

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ABSTRACT

Connected autonomous vehicles have boosted a high demand on communication throughput in order to timely share the information collected by in-car sensors (e.g., LiDAR). While visible light communication (VLC) has shown its capability to offer Gigabit-level throughput for applications with high demand for data rate, most are performed indoors and the throughput of outdoor VLC drops to a few Mbps. To fill this performance gap, this paper presents RayTrack, an interference-free outdoor mobile VLC system. The key idea of RayTrack is to use a small but real-time adjustable FOV according to the transmitter location, which can effectively repel interference from the environment and from other transmitters and boost the system throughput. The idea also realizes virtual point-to-point links, and eliminates the need of link access control. To be able to minimize the transmitter detection time to only 20 ms, RayTrack leverages a high-compression-ratio compressive sensing scheme, incorporating a dual-photodiode architecture, optimized measurement matrix and Gaussian-based basis to increase sparsity. Real-world driving experiments show that RayTrack is able to achieve a data rate of 607.9 kbps with over 90% detection accuracy and lower than 15% bit error rate at 35 m, with 70 - 100 km/hr driving speed. To the best of our knowledge, this is the first working outdoor VLC system which can offer such range, throughput and error performance while accommodating freeway mobility.

CCS CONCEPTS

• **Networks** → **Mobile networks**; • **Hardware** → **Signal processing systems**.

KEYWORDS

Visible light communication, Vehicular communication, Compressive sensing

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Figure 1: RayTrack dynamically adjusts its FOV to set up point-to-point links to desired transmitters.

1 INTRODUCTION

Platoon formation of connected autonomous vehicles (CAVs) are foreseen to serve a crucial role in the next-generation intelligent transportation system (ITS), creating a more efficient and accident-free driving environment. Vehicles in a CAV leverage cooperative sensing to synchronize the perception, maintaining full awareness of the driving environment in order to avoid sight blockage [29]. Moreover, communications between the CAV and the infrastructure such as the traffic light, can further extend the scope of its perception [31].

Though sharing sensor information such as those from Radar, camera and LiDAR would significantly enhance road safety, it induces a high demand for communication throughput, e.g., per vehicle, 5 Mbps is required for full HD video streaming and 50 - 350 Mbps is required for LiDAR raw data [27, 29]. Many existing and developing solutions are radio frequency (RF) based and omnidirectional in nature; in dense deployment, bandwidth is divided among the users and severe mutual interference could further hinder system throughput as well as the latency.

On the other hand, VLC has been envisioned as an appealing network paradigm for outdoor and vehicular communications [28], which can complement RF-based communications and make up for its shortcomings. The advantages of VLC are twofold. First, thanks to the inherent line-of-sight optical propagation property, there is limited interference even in a dense communication network [38]. Second, VLC exhibits a very slowly varying channel in outdoor and mobile environments, and hence offers better reliability than the RF-based communication in these scenarios [12].

Past research on VLC has demonstrated its potential to deliver high bandwidth connectivity with Gigabit-level throughput [14, 20]. Nevertheless, most existing works with Gigabit-level VLC links are realized in indoor environments with a communication range no longer than 1.5 m and in stationary settings, while most outdoor VLC implementations produce a throughput no more than a few Mbps [7]. There are two main reasons for such a significant performance gap. First, in outdoor VLC, the communication range can be up to 100 m, causing huge propagation loss. Second, the outdoor optical noise is considerably more severe. One general technique to deal with both of these problems is to *narrow down the field-of-view (FOV) of the receiver*, reducing incoming optical noise to improve signal-to-noise ratio (SNR). Yet, this is *at the expense of constraining the mobility between the transmitter and the receiver*.

In this paper, we set out to break this compromise between interference mitigation and limited mobility, which is the first step to realize high-throughput outdoor VLC. We introduce RayTrack, an interference-free point-to-point VLC system which enables access-control-free concurrent transmission. RayTrack can perform fast detection of transmitters within its full FOV, namely **detection FOV**. Once the location of the transmitter is known (see Fig. 1, detection state), the narrowed-down **communication FOV** is configured in real time to allow only the light signal from a particular transmitter to enter the receiver (see Fig. 1, communication state).

RayTrack offers several nice benefits for outdoor VLC. First, during communications, tight FOV *repels severe ambient interference* such as solar radiation, which can significantly boost the system throughput (see Sec. 2.3). Second, *interference from other transmitters is also eliminated*, providing monopoly bandwidth to support vehicle platooning [32] as well as vehicle safety applications. Third, RayTrack *waives the need of a link access control mechanism*. With VLC, link asymmetry between the two communication devices can be significant [35], traditionally requiring heavy protocol to address the hidden terminal problem. RayTrack avoids this by leveraging tight communication FOV to create virtual point-to-point links at the physical layer. In addition, realizing this spatial multiplexing capability at the receiver side instead of the transmitter side also avoid changing the output patterns of the transmitters (e.g., taillights or headlamps), which are constrained by the safety regulations.

RayTrack is motivated by single-pixel imaging [34, 39]. It makes use of dual photodiodes (PDs) and a digital micromirror device (DMD) as the spatial light modulator (SLM). These are leveraged in compressive sensing (CS) to recover the observed scene within its detection FOV. However, our goal differs from conventional single-pixel imaging, which aims to restore high-quality images. Instead, *only the locations of the transmitters are needed*. The simpler goal provides great opportunity to cut down the detection time to the limit, corresponding to a compression ratio (see definition in Sec. 2.1) much higher than those reported in prior works [34, 39], i.e., up to 20. This allows RayTrack to cope with *high mobility* and reduce overhead for communications.

We realize RayTrack with a number of key design elements. First, *making use of two PDs* (Sec. 3.2) allows the system to collect more information about the observed scene with the same number of measurements. In addition, environmental noises in the two received signals are highly correlated and they can be eliminated via proper post-processing. Second, to improve robustness, we also

optimize the measurement matrix using empirical data (Sec. 3.3), with which RayTrack is able to reliably detect the transmitters with high compression ratio. Third, in CS, the required number of measurements for signal reconstruction grows with reduced sparsity of the signal. When *multiple transmitters* are present in the FOV, as the observed scene is no longer as sparse as when there is only a single transmitter, offering the same detection accuracy with the same compression ratio is no longer possible. To cope with this challenge, we model the spatial power distribution of the transmitter's projection on the SLM with empirical data. Based on this, a Gaussian-based basis (Sec. 3.4) is developed to increase the sparsity of the signal. This enables reliable detection in multi-transmitter scenarios.

Building the RayTrack prototype with COTS DMD, PD, and the USRP N200 software radio platform, we also resolve many practical issues (Sec. 4). The reflection light path of DMD is modeled, such that optical components can be chosen to balance between detection FOV and aperture, maximizing the received optical power with a fixed FOV. Also, communication FOV size is determined based on the analysis of the lateral movements of cars in front in real-world driving scenarios. Benchmark experiments as well as real-world driving experiments are carried out to verify the performance of RayTrack (Sec. 5 and Sec. 6). Our key findings include:

- In stationary settings, RayTrack achieves over 98% detection accuracy with 19 ms detection time at 45 m.
- Dual-PD architecture improves the detection time for 95% detection rate by up to a factor of three, compared to single-PD architecture.
- Zero-missing detection is achieved with our proposed pre-learn measurement matrix using only half of the detection time required by random matrix.
- The proposed Gaussian-based basis effectively improves the sparsity under multi-transmitter scenarios. Transmitters with strongest received power can be robustly detected within detection time of 11.5 - 19 ms.
- In real-world freeway driving scenario, with 70 - 100 km/hr speed, RayTrack achieves a data rate of 607.9 kbps with over 90% detection accuracy and bit error rate (BER) less than 15% at a distance of 35 m. To the best of our knowledge, RayTrack is the first working outdoor VLC system to work with this level of mobility and with such performance.

2 BACKGROUND

2.1 Compressive Sensing

Compressive sensing (CS) is an efficient signal acquiring technique to obtain and reconstruct signals with the number of measurements less than that required by Shannon-Nyquist sampling theorem. This nice property holds if two conditions are fulfilled. First, the signal needs to be *sparse* or *compressible* in some basis or transformation domain, namely that most basis coefficients are zero-valued or nearly zero. Second, the transformation basis has to be incoherent to the measurement matrix [17].

Mathematically, consider a real-valued signal x of length N to be recovered. Suppose that x has a K -sparse representation provided

by a known basis $\Psi = [\psi_1 \psi_2 \dots \psi_N]$, then x can be described as

$$x = \sum_{i=1}^N \alpha(i) \psi_i = \Psi \alpha, \quad (1)$$

where Ψ is an $N \times N$ matrix with ψ_i as columns and α is an $N \times 1$ coefficient vector with K nonzero entries ($K \ll N$). In CS, it states that this K -sparse signal α can be reconstructed from at least $\hat{m}$ linear measurements, with a set of measurement matrix, where $\hat{m}$ is given by [17]

$$\hat{m} = O(K \log \frac{N}{K}). \quad (2)$$

With Eq. 1, the measurement process can be expressed as

$$y = \Phi x = \Phi \Psi \alpha, \quad (3)$$

where y is an $m \times 1$ measurement intensity vector, and Φ is an $m \times N$ measurement matrix; here, we also define *compression ratio* η as the ratio of the total signal length N to the number of measurements m , expressed as

$$\eta = \frac{N}{m}. \quad (4)$$

To fulfill the assumptions of CS, the measurement matrix Φ need to be chosen properly so that it cannot sparsely represent the entries of basis Ψ (i.e., Φ and Ψ are incoherent). It has been shown that if the above condition holds, then α can be well recovered using l_1 minimization [9, 10, 17]:

$$\min_{\alpha} \|\alpha\|_1 \quad s.t. \quad y = \Phi \Psi \alpha. \quad (5)$$

This is a convex optimization problem known as basis pursuit (BP) [30], which can be solved with linear programming techniques. On the other hand, since that y might be noisy in practical use cases, BP can be modified to be basis pursuit denoising (BPDN), expressed as [13]:

$$\min_{\alpha} \frac{1}{2} \|y - \Phi \Psi \alpha\|_2^2 + \lambda \|\alpha\|_1, \quad (6)$$

where the first term calculates the reconstruction error and the second term represents sparsity. BPDN trades off small reconstruction error with the sparsity of α . When λ is well-chosen, BPDN is able to accommodate noise and enhance the sparsity of recovered α .

RayTrack leverages CS to minimize the number of measurements m for transmitter detection, reducing the detection time. The intuition is that the transmitters only occupies a handful of locations while the rest of detection FOV is “empty”, and therefore the signal is sparse in nature. We discuss these details in Sec. 3, while performance comparison when using BP and BPDN is presented in Sec. 5.2 and Sec. 5.3.

2.2 Digital Micromirror Device

A digital micromirror device (DMD) is an optical micro-electrical-mechanical system which contains an array of millions of micromirrors. Each micromirror, also called pixel, can be tilted $\pm 12^\circ$ or $\pm 17^\circ$ and directs the incoming light to two different directions. Specifically, a $+12^\circ$ tilt is referred to as the *ON* state and a -12° tilt is referred to as the *OFF* state. To configure the states of the pixels, a binary pattern (i.e., image), where “1” represents for the *ON* state and “0” represents for the *OFF* state, is uploaded to the memory of a DMD. Typically, it takes 0.25 - 0.9 ms to upload a pattern [36], which

would become a significant overhead degrading system throughput if patterns need to be uploaded in real time for detection.

DMD is a key component in the RayTrack receiver for both FOV adjustment and transmitter detection. Since it is electronically controlled and has excellent latency of tens of microseconds¹, RayTrack is able to quickly set the FOV to alternate between different transmitters (Fig. 1). It also allows us to quickly perform CS to detect transmitters, accommodating transmitter mobility.

It is worth noting that, although DMD attenuates the reflected light by 30% to 50% with respect to the input, the attenuation applies to both signal from the transmitter and ambient light. Even when the DMD is configured to redirect all light toward a single direction, i.e., utilizing full FOV, SNR is only slight reduced compared to when not using DMD in a VLC system [4]. In the next subsection, we will illustrate how smaller FOV can significantly improve the SNR.

2.3 Reducing FOV to Improve SNR

Solar radiation is the dominant interference for outdoor VLC. Under an environment with intense solar radiation, a receiving PD would easily get saturated, resulting in communication failure. Most energy from the solar radiation is close to direct current (DC) in frequency, and can be easily removed by an electrical bandpass filter [38]. However, in this case, the shot noise induced by the solar radiation becomes a dominant noise source, impairing the communication performance.

The SNR of a VLC system, denoted by Γ , is given by [24]

$$\Gamma = \frac{\gamma^2 P_{\text{signal}}^2}{N}, \quad (7)$$

where γ is the responsivity of the PD, P_{signal} is the received optical power of the desired signal, and N is the total noise variance, which is an additive white Gaussian noise (AWGN), contributed by the shot and the thermal noise and given by

$$N = \sigma_{\text{shot}}^2 + \sigma_{\text{thermal}}^2. \quad (8)$$

The shot noise is given by

$$\sigma_{\text{shot}}^2 = 2q\gamma P_{\text{signal}}B + 2q\gamma P_{\text{bg}}I_2B \quad (9)$$

where q is the electronic charge (1.602×10^{-19} C), B is the system bandwidth, P_{bg} is the received optical background power, and $I_2 = 0.562$ is the noise bandwidth factor for the background noise [22]². From Eq. 9, we know that shot noise is proportional to the received background power. Thus, by reducing the size of the receiver FOV, we can also reduce the received background power, minimizing the shot noise within the received signal, and hence improve the SNR.

To verify this intuition, we measure P_{bg} in outdoor environments under different weather conditions: sunny, mostly sunny, sunset and cloudy. A spectrum analyzer is used to measure the electrical power within RayTrack’s 2.5 MHz communication bandwidth, given by

$$P_{\text{el}} = \frac{(\gamma G P_{\text{bg}})^2}{50}, \quad (10)$$

where G is the transimpedance gain of the built-in amplifier of the PD and the value 50 is the standard RF transmission line impedance.

¹RayTrack’s DMD has a mirror switching time of 13 - 22 μ s.

²As shot noise is dominant, here we do not give the equation of thermal noise due to space limit, and refer the readers to [22] for details.

Figure 2: Received optical background power P_{bg} with different FOV sizes under different weather conditions.

Table 1: Estimated / measured received optical power (dBm).

Transmitter LED	20 m	40 m	80 m
Headlamp LED	-28.67 ³	-34.69	-40.71
RayTrack TX	-47.59 ³	—	—
Taillight LED	-51.53 ³	—	—

With Eq. 10, P_{bg} can be calculated. Fig. 2 compares the received background power P_{bg} with thirteen FOV sizes. One can observe that P_{bg} grows linearly with the FOV size, though with different slopes. On sunny days, small FOV can significantly reduce the noise power, by as much as 10 dB.

To see the improvement made by small FOV on a sunny day, we conduct a simple numerical analysis on the spectral efficiency under different SNR using the previously mentioned empirical data. Table 1 shows the estimated and measured received optical power at different distances using off-the-shelf LED headlamp, taillight and RayTrack transmitter. SNR is calculated based on these values, and the shot noise power can be determined by the bandwidth and the FOV size. Assuming the use of forward error correction (FEC) code capable of eliminating errors with BER lower than 3.8×10^{-3} , we can determine the throughput of highest-possible-order single-carrier QAM modulation. Then, the spectral efficiency under these assumptions can also be calculated.

Fig. 3 shows that spectral efficiency *can increase by up to 5 bit/Hz with the smallest FOV*. In some cases, e.g., taillight transmitter with 2.5 MHz bandwidth, while communication with large FOV cannot take place, it can still be established with the smallest FOV. This encouraging result demonstrates the potential of RayTrack to realize high-speed outdoor VLC compared to conventional solution. In order to accommodate mobility, in the next section we will discuss how to detect the transmitter location and move the FOV accordingly.

3 SYSTEM DESIGN

3.1 Overview

The primary design objective of RayTrack is to allow fast and robust tracking of multiple mobile transmitters. Once this is achieved, the size of the communication FOV is reduced to only contain a single

³Measured with RayTrack prototype.

Figure 3: Spectral efficiency with different FOV sizes on a sunny day.

transmitter, such that most interference is optically removed from the received signal, creating virtually a *point-to-point link*.

Our system is built upon the architecture of single-pixel imaging [34], consisting of an imaging lens, a DMD (as the SLM) and two PDs, as shown in Fig. 4. The imaging lens projects the scene within detection FOV onto the DMD, such that each DMD pixel corresponds to a small piece of FOV. The *ON* and *OFF* states of each pixel (i.e., micromirror) redirects the incoming light from that small piece of FOV into either the *ON*-state PD or *OFF*-state PD.

As shown in Fig. 1, RayTrack alternates between two states: *detection* and *communication*. In *communication* state, the system would configure the FOV of the receiver to match the location of the transmitter of interest. This is achieved by setting the pixels mapping to the location of the receiver to *ON* state and redirecting light into *ON*-state PD. All other pixels would be set to *OFF* state and redirect light into *OFF*-state PD. Signal would be collected by *ON*-state PD for a fixed time period for decoding, while those collected by *OFF*-state PD, i.e., interference from other locations, would be discarded. If multiple transmitters are detected, the receiver would take turn to collect their signals in a round-robin and time-division manner. To know the positions of the transmitters of interest, in *detection* state, RayTrack finds pixels with high intensity values at specific frequencies. As useful communications only take place in *communication* state, much of our efforts is devoted to *minimizing the detection time*, leveraging dual-PD architecture with CS techniques in Sec. 3.2, pre-learn measurement matrix in Sec. 3.3, and Gaussian-based basis in Sec. 3.4.

3.2 Detection with Dual PDs

To detect the transmitter location, RayTrack uses its PD and DMD to “take a picture” of the scene within its detection FOV (i.e., full FOV), as shown in Fig. 4. However, there are two fundamental differences compared to those taken with regular cameras. First, this picture is taken *at the carrier frequency*, with bright regions indicating high received signal power at that location and mostly black background. This is due to the fact that energy from various light sources and their reflections mostly reside at DC and lower frequency range. Second, since the goal is to detect the location of

Figure 4: RayTrack's optical system design.

the transmitter, slight inaccuracy of this “taken picture” would not affect the detection accuracy.

Without an image sensor, the most naïve way for a single-imaging device such as RayTrack to take such picture, is to sequentially measure the pixel intensity. However, even with a small number of pixels, it still takes significant amount of time to do so⁴.

The two previously mentioned fundamental differences create opportunities to speed up the process, leveraging CS, as described in Sec. 2.1. Moreover, these two properties allow higher compression ratio⁵, since the signal is very sparse, i.e., most background pixels are zero- or small-valued, and the detection process is resilient to error produced by CS. As higher compression ratio directly translates to lower detection latency, we therefore aim to maximize it. Here, we further increase the compression ratio with a dual-PD design.

Specifically, the transmitter detection problem can be formulated as a classic CS problem. According to Eq. 3, we have

$$y = \Phi x + N_0, \quad (11)$$

where Φ is an $m \times N$ measurement matrix, x is an $N \times 1$ vector corresponding to the “taken picture”, reshaped from 2D to 1D vector, y represents an $m \times 1$ measurement intensity vector collected by the PD and N_0 is the noise. x can then be solved using BP or BPDN.

To perform CS using DMD, RayTrack adopts partial Hadamard matrix [40] as its measurement matrix, which has 1/-1 entries. The measurement matrix Φ is first split into vectors $\phi(i)$ with size $N \times 1$, $i \in 1, 2, \dots, m$, denoted as pattern hereafter. For the i -th observation, pattern $\phi(i)$ is reshaped to a 2D array to be displayed on DMD for a certain amount of time, i.e., measurement period. Finally, we can derive measurement intensity $y(i) = \langle x, \phi_i \rangle$ by averaging the power of received samples during the i -th observation.

In the literature, CS is usually performed with one PD, denoted as single-PD hereafter. With single-PD, -1-valued entries in the measurement matrix Φ is zeroed out to become a binary matrix with 0 and 1 entries. The pixels corresponding to 1 entries would redirect light to ON-state PD while those corresponding to 0 entries would redirect light to be *discarded*. The key question is, *can we recycle*

the discarded signal to collect more information and further increase the compression ratio?

The answer is yes! To realize the idea, a second PD, i.e., OFF-state PD is installed and leveraged, using complementary compressive imaging (CCI) [39].

First, the Hadamard measurement matrix Φ is split into

$$\Phi^+ = \frac{I + \Phi}{2} \quad \text{and} \quad \Phi^- = \frac{I - \Phi}{2}, \quad (12)$$

where I is an identity matrix and $\Phi = \Phi^+ - \Phi^-$. Both Φ^+ and Φ^- are binary matrices with 0/1 values. Then, the measured intensity vectors of both PDs y_1, y_2 are given by

$$y_1 = \Phi^+ x + N_1, \quad y_2 = \Phi^- x + N_2, \quad (13)$$

where x is the vector representing the observed “picture”, and N_1 and N_2 respectively represent ambient noise observed at the two PDs and are integrated over measurement period. Since the ambient noise can be assumed to be uniformly distributed, i.e., $N_1 \approx N_2$, subtracting y_2 from y_1 would allow us to mitigate the noise terms:

$$y = y_1 - y_2 = (\Phi^+ - \Phi^-) x + (N_1 - N_2) \approx \Phi x. \quad (14)$$

Due to the increased amount of information in y and reduced noise level, our results indicate that compression ratio can be further increased to 20 with the dual-PD design.

3.3 Measurement Matrix Optimization

Most existing works in single-pixel imaging randomly select m vectors out of $N \times N$ full measurement matrix, i.e., in our case, Hadamard matrix, as its measurement matrix Φ [8, 18]. However, RayTrack deals with very sparse signal and makes attempts to use very high compression ratio - 20. *Is there a different way to construct the measurement matrix which offers better reconstruction performance?*

To answer the question, we made the following observations: selection of vector $\phi(i)$ in the measurement matrix Φ tends to produce better reconstruction results if the intensity of that measurement $y(i)$ is large. Furthermore, it seems reasonable to assume that a number of vectors $\phi(1), \dots, \phi(n)$ would have higher likelihood to produce larger measurement values given the range of scenes RayTrack would observe, and those would be good candidates which Φ should include.

To obtain the selection of Φ which can allow higher compression ratio, we propose the following to *pre-learn* it. We collect our training data set in an outdoor scenario with only one transmitter in the FOV and the distance between the transmitter and receiver is 45 m, which is close to the maximum range. The transmitter is placed approximately in the center of RayTrack's detection FOV. We collect the measurement intensity for all the N patterns in the full Hadamard matrix, and repeat this procedure for 100 times. Then, we rank the performance of each pattern by normalizing and summing up the measured intensity. Finally, the m patterns with the highest measured intensity are chosen to construct the pre-learn matrix Φ . Note that since this pre-learn matrix remains unchanged in RayTrack's detection process, we can pre-load the matrix to the DMD. As a result, no extra time is required for pattern uploading during detection state.

⁴In RayTrack prototype, we group adjacent 32x32 pixels into larger *macro-pixels* to reduce the total number of pixels. Even with this configuration, taking a picture with sequential scan would take $768 \cdot 0.5 \text{ ms} = 384 \text{ ms}$.

⁵Single-pixel imaging device taking regular pictures at DC can usually obtain good results with 4 - 6.67 compression ratio, compared to 10 - 20 used by RayTrack.

3.4 Gaussian-based Basis

Eq. 2 provides a critical insight - the required number of measurements to reconstruct the original signal depends heavily on the sparsity of the signal. In our case, the number of transmitters within RayTrack's detection FOV determines the sparsity of the signal. However, a few challenges prevent us from increasing the compression ratio, i.e., reducing the number of measurements, to the limit. First, the number of transmitters within the detection FOV, denoted by T , is unknown to the receiver during the detection state, and thus it is difficult to dynamically adjust the number of measurements. Second, although most energy of the projection of the transmitter falls into a single macro-pixel, there is still leakage to its neighboring macro-pixels, as shown in Fig. 4. This results in decreased sparsity of the signal, i.e., $K > T$, implying that an even higher number of measurements is required for accurate reconstruction and detection. *Given there are multiple transmitters, how do we enhance the sparsity of the signal to avoid this?*

The solution is in Eq. 1 in Sec. 2.1. Selecting a proper basis Ψ for our detection scene, we are able to create a signal with better sparsity for reconstruction. The intuition is that, if the projection patterns of the transmitters have similar shape, a proper basis capturing the shape would be able to condense the signal coming from a single transmitter to less or even just one entry in x , i.e., bringing sparsity K closer to T .

To determine the projection pattern, we collect the received power distribution within a 9×9 macro-pixel area at detection distance ranging from 10 to 45 m. At each detection distance, 100 patterns are collected. Then, a two-dimensional, zero-mean Gaussian distribution is created to fit each of these distributions, with best values of horizontal and vertical variances. The variances of these fitted distributions are then averaged and used to create a discrete Gaussian-like 2D mask $G(x, y)$ of size 9×9 . In Eq. 1, $\Psi = [\psi_1 \psi_2 \dots \psi_N]$, where ψ_i is one dimensional vector and represents the case where the transmitter is located at the i -th pixel. We first reshape vector ψ_i to a 2D matrix $\psi'_i(j, k)$ with size $p \times q$, where the i -th pixel corresponds to (a_i, b_i) in $\psi'_i(j, k)$. Then, we can derive $\psi'_i(j, k)$ for all possible values of j, k using G:

$$\psi'_i(j, k) = \begin{cases} G(j - a_i + 5, k - b_i + 5), & \text{if } |a_i - j| < 5 \\ & \text{and } |b_i - k| < 5 \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

Finally, we can reshape these $\psi'_i(j, k)$ back to ψ_i and produce the required basis Ψ .

4 IMPLEMENTATION

4.1 Transmitter

The transmitter comprises an MR16 LED [5], a software defined radio USRP N200, a VLC front-end board and a laptop. The laptop is used to generate 64-subcarrier OFDM waveform with 48 data and 4 pilot subcarriers, pre-equalized before transmission to compensate for non-linear LED frequency response. The signal uses 2.5 MHz of bandwidth, and the USRP transmits the signal with center frequency 1.6 MHz. A VLC front-end board is used to drive the LED according to the USRP output.

4.2 Receiver

Overview. Fig. 5 shows the prototype of RayTrack, comprising two convex lenses, two condenser lenses, a DMD and two PDs. A Vialux V-7001 [36] with a 12° tilt angle and a resolution of 1024×768 is used. We group adjacent 32×32 pixel areas into macro-pixels, reducing the effective resolution to 32×24 . Note that this required resolution can be satisfied with almost all low-cost DMD products on the market, with the cheapest costing only USD\$20 at the time of writing.

Since the micromirror's rotation axis is its diagonal, the DMD is rotated 45° counter-clockwise so that the reflection light paths to the ON- and OFF-state PDs, both are Thorlabs PDA100A2 PDs, can be on the same horizontal line. The PDs are placed such that the angle between the normal of PD receiving area and the normal of DMD is 24° , matching incoming the reflection paths. A Thorlabs ACL50832U-A condenser lens is placed in front of each PD to concentrate the incoming light signal onto the PD active area. Behind each PD, a mini-circuit BLK-89-S+ DC block is inserted to add more than 30 dB loss to signal below 100 KHz. Finally, a USRP N200 is used to sample the signals collected by the two PDs with sampling rate of 2.5 MHz and center frequency of 1.6 MHz, which are then processed by a laptop.

Trade-off between detection FOV and aperture. Larger FOV allows RayTrack to offer a more peripheral vision, and to establish more communication links, whereas larger aperture gathers more light for better SNR. Here we briefly discuss the trade-off between FOV and aperture in RayTrack design.

Given a DMD with a certain size, shorter focal length of the imaging lens produces larger FOV. On the other hand, aperture is determined by the diameter of the imaging lens, bounded by the focal length as well as the dimensions of other system components and reflection light paths. Specifically, the reflection light paths of the DMD cannot be obstructed by the lenses to create additional signal attenuation.

To balance between these two parameters, we model the incident and reflection light paths with the maximum incident angle to determine the optimal relationship between the focal length and diameter of the imaging lens. While there are multiple rays projected on the DMD, as an approximation here we only model the incident ray passing through the center of the lens. As shown in Fig. 6, the largest incident angle θ happens when the incident ray emits on the rightmost and leftmost pixel of DMD, namely ray (a) and (b). We can derive θ by

$$\theta = \tan^{-1} \left(\frac{w}{2d} \right), \quad (16)$$

where d is the distance between the lens and the DMD, and w is the horizontal distance between the rightmost pixel and the leftmost pixel of the DMD. Without loss of generality, we take ON state as an example; the incident ray (a) and (b) would result in reflection angles of $24 - \theta$ and $24 + \theta$, respectively. As case (a) uses light paths closer to the imaging lens, it constraints the size of the imaging lens, whose diameter should be determined accordingly, given by

$$\tan(24 - \theta) \times d \geq \frac{l + w}{2}. \quad (17)$$

where l is the diameter of the imaging lens, including the lens mount. Note that when using one lens as the imaging lens, d equals

Figure 5: RayTrack receiver prototype.

Figure 6: An illustration of light paths when the light emit on border pixels of DMD.

Figure 7: RayTrack's detection FOV.

to the back focal length of the used lens. Whereas, when multiple lenses are combined as the imaging lens, d represents the distance between the DMD and the lens closest to the DMD. In addition, we have θ bounded by the degree of the tilt angle (i.e., 12°). This is because that if the light (a) in Fig. 6 has a θ is larger than 12° , the incident light path would be on the left hand side of the normal to the ON state, directing the light towards the imaging lens instead of the PD. Eq. 17 dictates the trade-off between the diameter and the focal length of the imaging lens.

Based on these observations, we use a 30 mm convex lens with 100 mm focal length (Thorlabs LA1031-A) and a 2" convex lens with 200 mm focal length (Thorlabs LA1979-A) to create an optical system with 37.5 mm effective aperture and 75 mm effective focal length, corresponding to a horizontal FOV of 10.68° and a vertical FOV of 8.02° . As illustrated in Fig. 7, such FOV can cover a lateral distance of 3.7 m at 20 m longitudinal distance. Thus, a transmitting car taking right and left turns or making lane changes would be covered by the detection FOV if the longitudinal distance is larger than 20 m. Wider FOV can be achieved with DMD with larger tilt angle or custom designed optical systems.

CS implementation.

Measurement matrix. Based on the effective resolution of RayTrack, we use a 768×768 Hadamard matrix as the measurement matrix for CS, where each column of the matrix is a measurement pattern as mentioned in Sec. 3.2.

Measurement period. For each measurement pattern, the PD would collect and aggregate incoming light signal for a time period, namely, the measurement period. Shorter measurement period results in reduced detection time, but may be more prone to noise due to lower received power. A measurement period of 0.5 ms is empirically selected.

Frequency filtering. Since the transmitter continuously send OFDM signal, in detection state, RayTrack only measures power of frequencies used by the OFDM signal for CS reconstruction. A frequency filter is used to remove those outside of these frequencies.

Scene reconstruction and transmitter detection. After we derive the measurement intensities, we exploit the `L1eq_pd` function in `l1-MAGIC` [1] and `L1-Homotopy` [2] with $\lambda = 1.5$ to solve the BP and BPDN equations, respectively, obtaining the reconstructed

Table 2: Spatial resolution of RayTrack at 10 to 40 m.

Distance (m)	10	15	20	25	30
Pixel FOV (cm)	8.27	12.41	16.54	20.68	24.81

scene. It is worth noting that, Gaussian-based basis introduces large residuals if the projection of the transmitter is not exactly located in the center of the macro-pixel; BPDN is able to accommodate these residuals while making the reconstruction scene sparse by adjusting a proper λ value. Finally, in this reconstructed image, a threshold of 50% of the highest pixel intensity is used to locate transmitters.

Real-time operation. To examine the performance of RayTrack in real-world driving scenarios, we have implemented a Python program with multiple subprocess to deal with USRP sampling, DMD configuration, CS calculation and communications. The states of DMD is configured dynamically using ALP4lib programming library [3].

Communication FOV size selection. Small communication FOV size can eliminate more interference; however, when mobility is present, it is more likely that the transmitter would move out of the FOV. In this case, detection needs to be performed more frequently, reducing the communication throughput. To determine a suitable FOV, we collect the traces of the vehicles in front on a freeway using LiDAR, and analyze the relative lateral moving speed. The results show that the 95-th percentile of the moving speed is about 1.6 m/sec. If we assume a detection rate of 5 Hz, the possible shift of the front vehicle between detections would be 64 cm. Table 2 shows the FOV of one macro-pixel at different distances. Note that the pixel FOV stands for the length of the diagonal of a macro-pixel which is parallel to the lateral movements (see Fig. 5). According to the table, we choose a FOV size of 5×5 macro-pixels, which can accommodate possible shift with distance larger than 15 m.

5 BENCHMARK

This section presents benchmark results using our RayTrack prototype, demonstrating its ability to mitigate interference and reliable detection of either single or multiple transmitters. These experiments are carried out in stationary scenarios.

Figure 8: VLC link in outdoor and sunny environment.

Figure 9: BER performance with strong sunlight.

Figure 10: BER performance with interference from other transmitter.

Figure 11: BER at different locations with respect to the communication FOV.

5.1 Interference Rejection

We first examine RayTrack's ability to mitigate interference and compare it with a typical VLC system, i.e., with fixed FOV. This is evaluated with two types of interference sources. First, solar radiation, which is the most challenging impairment introduced by outdoor environments. Second, the interference from other transmitter; in most cases there is likely more than one transmitter within the FOV, and therefore it is crucial that RayTrack is able to separate the signal of interest from the others.

Experimental setup: We set up only one transmitter in the FOV of the receiver. In the case of RayTrack, the system locks the position of the transmitter at the center of the communication FOV and the FOV size is configured to be 5×5 macro-pixels. In the case of the typical VLC system, it is emulated by using the full FOV of RayTrack (about $10.7^\circ \times 8^\circ$), setting all pixels of the DMD to redirect light into the ON-state PD. BER is calculated to evaluate the performance. To test how well the system can mitigate sunlight interference, the VLC link is deployed in an outdoor environment, as shown in Fig. 8. At the time the experiment was carried out, the measured sunlight luminance is about 20-100 klux, reported by a luminometer. The system is covered by a metal box to ensure optical isolation to external interference.

Separately, to evaluate how well RayTrack can cope with interference from other transmitter, an experiment is carried out in an indoor environment with a distance of 20 m. A jammer uses the same hardware and the same OFDM transmission format to transmit random information with the same transmission power, and is placed at the same distance as the transmitter. The transmitter is placed at the center of the detection FOV. We alter the location of the jammer to compare the communication performance as the distance between the projected position of the transmitter and that of the jammer on the DMD, ranging between 3 and 16 macro-pixels.

Results: Fig. 9 illustrates the BER performance at 5 to 45 m with sunlight interference. At each distance, we collected approximately 900 packets consisting of 3.4 Mbits in total. The results reveal great advantage offered by a reduced FOV size. Despite the use of a DC block, one can observe that strong sunlight still saturates the system with full FOV, represented by a BER of 0.5. On the other hand, RayTrack is able to *maintain a functional communication link at all distances*, as it selectively narrowed down the FOV to repel the inevitable sunlight interference.

Fig. 10 compares the BER of RayTrack and a typical VLC system with VLC when interference from the other transmitter is present. As a reference, BER without the jammer and with 5×5 macro-pixel FOV is also measured. The result shows that RayTrack is capable of isolating the signal from the transmitter of interest from the others. As shown in Fig. 10, the BER using RayTrack is similar to the one without interference, with the exception of the case with a distance of 3 macro-pixels. In this case, the projection of the jammer on the DMD is too close to the receiving FOV, i.e., the ON pixels directing light into the ON-state PD. Thus, part of the transmission power of the jammer would leak into the received signal, causing higher BER. On the other hand, producing a 0.5 BER, a typical VLC system using full FOV completely loses the communication link, as the transmissions from both the transmitter and the jammer are mixed into the received signal. These results show that *RayTrack is indeed capable of establishing virtually a point-to-point link, and eliminates the need to use an link layer access control mechanism.*

5.2 Single Transmitter Detection

Fast detection is achieved by RayTrack with three proposed techniques: dual-PD architecture, pre-learn measurement matrix and Gaussian-based basis. Here we evaluate the effectiveness of each technique with different distances and different compression ratios, with one transmitter in the FOV.

Experimental setup: The experiments are carried out in the outdoor environment shown in Fig. 8. The received intensities of both ON-state and OFF-state PDs of all 768 measurement patterns are collected, and repeated for 100 times for each test distance. Then, the measurement vector y (as introduced Sec. 2.1) is derived for the following settings: (1) PD usage: single left PD, single right PD or dual PD; (2) measurement matrix: random matrix or pre-learn matrix. Combining the two, there are six different cases.

In the cases of random measurement matrix, 1000 random measurement matrices are generated and used to obtain y , such that evaluation is performed with a large number of possible matrices and without bias. The pre-learned measurement matrix (shown in Sec. 3.3) is used for all other cases. Three CS solvers which are L1eq_pd with identity basis, L1eq_pd with Gaussian-based basis and L1-Homotopy with Gaussian-based basis, are applied to obtain the detection results, which is the estimated position of the transmitter on the DMD.

Figure 12: Comparison of detection performance using compression ratio ranging from 10 to 51.2 at 30 m (Time: detection time in ms, Ratio: compression ratio).

Figure 13: Comparison of detection performance at 5 to 45 m with a compression ratio of 20.2.

To quantify the detection performance, we first measure the BER at 20 m when the transmitter's projection falls on different location on the DMD, as presented in Fig. 11. The result shows that the BER rises dramatically, once the transmitter falls out of the FOV. Therefore, the acceptable detection error should be determined by the selected communication FOV size, which is 5×5 macro-pixel in our setting. Then, we calculate the *error distance*, which is the Euclidean distance between the estimated location and the ground truth location⁶ of the transmitter on the DMD, in macro-pixel. While the largest distance between the center of the FOV and the FOV border is $2\sqrt{2}$, detection results with error distance smaller than $2\sqrt{2}$ is considered successful detection. Eventually, we can evaluate the system with *detection rate*, which is the ratio of the number of successful detection to total detection trials.

Results: We first compare the detection performance of nine different compression ratios, from 10 to 51.2, as shown in Fig. 12. The results demonstrate significant improvement with our proposed dual-PD architecture over the single-PD alternative, and with the proposed pre-learn measurement matrix over the conventional

random matrix. For all three CS algorithms, it can be seen that dual-PD can often achieve the same detection rate with much higher compression ratio. For example, with L1-Homotopy with Gaussian-based basis, 23 ms detection time is required for a detection rate of 95% using single PD, while only 7.5 ms is required using dual PD, reducing the detection time by *a factor of three*. The same can be said for pre-learn matrix. For example, to reach 100% detection rate, dual-PD with random matrix require at least 23 ms detection time, while only 11.5 ms is required when using pre-learn matrix, reducing the detection by *a factor of two*. One can observe that single-PD with pre-learn matrix can often achieve the same performance as dual-PD with random matrix. One can also observe that with the help of Gaussian-based basis, dual-PD architecture with random measurement matrix can achieve a detection rate of about 80% at the cost of 11.5 - 15 ms detection time. Whereas, to achieve similar detection performance when using identity matrix, a detection time of 23 ms is needed. Based on these results, in the following evaluations, we set the compression ratio to 20.2, corresponding to 19 ms detection time, as the default setting.

We then compare the detection performance with a compression ratio of 20.2 at different detection distances. Fig. 13 compares the detection performance of different cases using the same three CS algorithms. The results confirm that dual-PD with pre-learn matrix

⁶We obtain the ground truth of the transmitter location by setting the transmitter to use high transmission power and performing CS detection with received intensity values of all 768 patterns, i.e., no compression.

always achieves better performance at all distances, regardless of the CS algorithm used. For dual-PD, the use of pre-learn matrix can extend the zero-missing detection range by at least 10 m, compared to random matrix. In addition, the detection performance of L1-Homotopy with Gaussian-based basis makes slight improvement over the other two algorithms at long distances. As we will see in the next subsection, larger progress is made by this algorithm for detecting multiple transmitters. Therefore, it is chosen as the main algorithm for real-world driving test, presented in the next section.

5.3 Multiple Transmitter Detection

Experimental setup: The following experiments with multiple transmitters are carried out with dual-PD architecture using pre-learn matrix in an indoor environment. Four asynchronous transmitters are configured to use the same OFDM format and the same carrier frequency. They are deployed in seven different spatial configurations with different positions and distances ranging from 20 - 25 m. For each configuration, we collect the received intensity for all 768 patterns and repeat this process for 100 times.

Results: The four transmitters in each configuration are sorted by received power. Fig. 14 compares the mean and standard deviation of the detection rate of the transmitters with the strongest and weakest received power under different compression ratios. The results verify that Gaussian-based basis is able to enhance the sparsity of the signal, and increase the compression ratio while maintaining the same detection performance. When adopting larger than 11.1 compression ratio, better performance are achieved using the two algorithms with Gaussian-based basis. Specifically, the detection time for zero-missing detection is reduced by 7.5 ms, for the transmitter with strongest received power. The transmitter can robustly be detected with 16.7 to 24.8 compression ratio. For the weakest transmitter, using L1-Homotopy with Gaussian-based basis performs better with small number of observations.

6 REAL-WORLD DRIVING RESULTS

In this section, we evaluate RayTrack in a real-world driving scenario, where it is deployed on test vehicles driving on a freeway. The experiments are carried out on a sunny day with a 13-km freeway segment with uphill and downhill slopes, curves and tunnels, as shown in Fig. 15. In this real-world driving experiment, we made six round trips, with a total driving distance of over 150 km and driving speed of 70 - 100 km/hr.

6.1 Experimental Setup

RayTrack is installed on two test vehicles, as shown in Fig 16. The receiver is installed on the roof of the following vehicle due to its large dimensions. A metal box is used to cover the receiver to provide protection against road dust and isolation from external optical interference. To maintain the same height for both the transmitter and the receiver, the transmitting LED is also mounted on the roof of the leading vehicle with a customized holder. In a real-world setting, we expect the transmitter to leverage the taillights as sources, while the receiver can be mounted on the front bumper.

Two supplementary components, a LiDAR and a camera, are adopted to obtain the ground truth. First, to correlate vehicle mobility with system performance, the relative positions of the vehicles

Figure 14: Comparison of detection performance with four transmitters using compression ratio ranging from 6.2 to 51.2 (Time: detection time in ms, Ratio: compression ratio, error bar: standard deviation).

have to be collected and synchronized with the detection and communication results. This is collected with a 2-dimensional LiDAR, SICK LMS-291, mounted on the front bumper of the following vehicle. Second, a camera is also mounted on the roof of the following vehicle for obtaining the transmitter location on the DMD as the ground truth. The following discusses how we obtain this ground truth.

Specifically, the projection of the transmitter on the DMD and the camera can be regarded as a 2D geometric transformation

$$T = \begin{bmatrix} s \cos \theta & s \sin \theta & 0 \\ s \sin \theta & -s \cos \theta & 0 \\ x_{\text{shift}} & y_{\text{shift}} & 1 \end{bmatrix}, \quad (18)$$

where s is the scaling factor, θ is the rotation coefficient and x_{shift} and y_{shift} are the translation coefficients. Ideally, if the vertical and horizontal plane of DMD and the camera are perfectly aligned, these coefficients should remain the same among different distance. However, in practical deployment, there exists a tilt angle between the camera and the DMD, and thus y_{shift} varies at different distances during our experiments. In order to obtain a general transformation model for various distances, we obtain nine transformation matrices $T_i, i = 1, 2, \dots, 9$, for every five meters from 5 to 45 m. Each transformation matrix is derived by nine pairs of control points between the DMD pixel and the camera image by placing the transmitter at nine different positions within the detection FOV of RayTrack. Since θ_i and $x_{\text{shift},i}$ should remain unchanged throughout the various distance, we obtain a θ and x_{shift} by averaging θ_i and $x_{\text{shift},i}, i = 1, 2, \dots, 9$. On the other hand, $y_{\text{shift},i}$ is proportional to the inverse of measured distance. As a result, we use the observed $y_{\text{shift},i}$ to fit a linear function of the inverse of distance. The average transformation error of the proposed method is 11.78 camera pixels, or, equivalently, 0.24 macro-pixel.

Figure 15: Driving route on Free-way No.3 in Taiwan.

Figure 16: System setup on testing vehicles.

Figure 17: Detection rate.

Figure 18: Communication BER.

To determine whether the detection is successful, we transform the coordinates of the detection results represented by DMD pixels into corresponding coordinates in camera pixels. Then, we calculate the distance between the detection result and the ground truth, denoted as error distance. The detection is considered to be a success attempt when the error distance is smaller than 123 camera pixels, i.e., the length of 2.5 DMD macro-pixels.

6.2 Results

Fig. 17 shows the detection performance under real-world driving conditions. In this figure, the receiver is assumed to be at origin, and the location of the cell represents the relative position of the transmitter with respect to the receiver. The detection rate is calculated for each 0.2 meter (lateral axis) by 1 meter (longitudinal axis) cell. The results show that RayTrack can achieve robust detection; within the lateral range from -1 to 1 m, most cells can achieve a detection rate of 90% to 100% for longitudinal distance up to about

35 m. At longer longitudinal distances, RayTrack can still produce detection rate of over 70%.

We also illustrate the detection performance according to the location of the projection on the DMD, as shown in Fig. 19. The detection rate is only calculated for locations with five or more data samples. The results demonstrate that the detection performance is robust regardless of which pixel the transmitter is projected on. Most pixels have good detection performance with over 80% detection rate with the exception of a small number of pixels with detection rate lower than 50%. We believe that these are caused by low number of received data for these pixels. Fig. 20 and Fig. 21 illustrates two examples with data collected from our driving experiments, with lane changing and turning maneuvers. With RayTrack configured with a detection rate of 3 to 4 Hz, it can be seen that successful detections can be carried out as the transmitter moves across the detection FOV for both types of maneuvers and at a lateral speed of 0.15 to 0.9 m/s. This shows that the detection latency of RayTrack is short enough to cope with the lateral movement of the transmitting car on the road.

In addition, Fig. 18 presents the communication performance when the transmitter is successfully detected. The data rate of our transmission format is 607.9 kbps. One can observe that RayTrack is capable of offering a reliable VLC link with a BER of 0% to 15% at a distance of 35 m and 25% to 30% at 45 m. Although we did not add FEC code in the packet in order to observe the behavior of the system, in practice this is often implemented to further increase range and robustness, at the cost of lower data rate.

7 RELATED WORK

Outdoor VLC. A number of literatures have focused on developing outdoor VLC, which can be divided into two categories based on their receiving component:

1) Photodiode-based: Kim et al. [23] presents a static VLC link with 500 kbps data rate at a communication distance of 20 m with a light shield and a red filter to avoid saturation under strong sunlight. To enhance the communication range, Corsini et al. [15] concentrates the output power of the transmitter to a divergence angle of 18° by adding a lens in front of the transmitter, reporting a data rate of 115 kbps at 31 m. Longer communication range are demonstrated in other works [6, 26], delivering a communication range of 40-50 m with 15-20 kbps data rate. Longer range of 1.2 km with 2 Mbps data rate is reported in [21], yet their system only allows a fixed,

Figure 19: Detection rate on DMD pixels.

Figure 20: Detection results when the front car changes to the right lane.

Figure 21: Detection results when the front car turns left.

very narrow FOV. To the best of our knowledge, no past works have demonstrated the feasibility of establishing reliable long-range VLC link with wide FOV to support high mobility scenarios.

2) Camera-based: Prior works on VLC using commodity camera have demonstrated a relatively short communication range of several meters with a data rate of a few kbps [16, 25]. This is mainly caused by the low temporal frame rate (30-120 fps) and low pixel occupancy at long distances. Nevertheless, cameras usually have high spatial resolution, allowing the receiver to differentiate multiple transmitters and filter out interference at different spatial locations. To this end, a series of researches [33, 37] have introduced a customized image sensor, consisting of communication and image pixels. The transmitters are located by image pixels and then the corresponding communication pixels are used to receive signals. Mobile experiments are carried out, showing a 10 Mbps data rate at distance and driving speed less than 20 m and 25 km/hr, respectively. However, the proposed system uses specialized sensor which is not commercially available. Our work aims to combine the advantages offered by photodiode-based and camera-based systems, namely high data rate, long communication range and the capability to distinguish multiple transmitting sources.

VLC system with DMD. Ghobadi et al. [19] incorporates a DMD and mirrors to build data center interconnects, enabling fast and flexible topology reconfiguration. A DMD is used to determine the reflection of the incoming light, directing the light to a proper receiver, improving the mean flow completion time by 30-95%. On the other hand, Chau et al. [11] introduces a MIMO VLC system utilizing DMD, where a binary search algorithm is used for initial detection of the location of TX. Following by a repeating tracking process, pixels near the initially detected TX location are turned on and off one by one to sense the change of the TX location. The evaluation carried out via simulations, with parameters chosen to match the prototype, shows that the proposed system outperforms traditional imaging VLC systems with lower channel matrix conditional number and higher rank. However, the patterns used by the binary search based detection algorithm (as well as the tracking algorithm) are determined and generated in real time, based on the received signal, and thus cannot be pre-uploaded. As uploading patterns to the DMD is a time-consuming operation, the added overhead to the latency is in the range of hundreds of milliseconds which would significantly reduce the system throughput. Inspired

by them, our work differs in that we introduce a fast transmitter detection mechanism. Our system also deal with real-world problems, and is proven with empirical evidence of results from high-speed driving scenarios.

8 CONCLUSION AND FUTURE WORK

In this paper, we present RayTrack, an interference-free point-to-point VLC receiver that enables access-control-free concurrent transmissions. RayTrack enables tight but real-time adjustable FOV in VLC receiver, which significantly improves a receiver's capability to repel interference from the environment and from other transmitters. To be able to track the transmitters, RayTrack maximizes the compression ratio in CS and achieves less than 20 ms detection time via multiple techniques: a dual-PD architecture to increase received information and mitigate noise, an optimized measurement matrix, and a Gaussian-based basis to enhance signal sparsity. Experimental results show that the RayTrack prototype can achieve over 98% detection accuracy at 45 m in static settings. In addition, the prototype was tested in a 70 - 100 km/hr speed driving scenario, where it demonstrates a data rate of 607.9 kbps, with over 90% detection accuracy and less than 15% BER at 35 m. To the best of our knowledge, RayTrack is the first outdoor VLC system that can deal with such level of mobility, while providing robust detection and communication performance.

The primary future direction lies in improving the data rate of RayTrack. Although our analysis indicates substantial throughput improvement over conventional solutions, the current implementation is constrained by the bandwidth of the chosen PD and LED components, i.e., ~800 kHz and the high noise floor of our system components. Better throughput performance is expected with PD and LED with larger bandwidth; the optical system may also need to be updated to accommodate PD with smaller active area.

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