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Performance analysis of ghost imaging lidar in background light environment

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The effect of background light on the imaging quality of three typical ghost imaging (GI) lidar systems (namely narrow pulsed GI lidar, heterodyne GI lidar, and pulse-compression GI lidar via coherent detection) is investigated. By computing the signal-to-noise ratio (SNR) of fluctuation-correlation GI, our analytical results, which are backed up by numerical simulations, demonstrate that pulse-compression GI lidar via coherent detection has the strongest capacity against background light, whereas the reconstruction quality of narrow pulsed GI lidar is the most vulnerable to background light. The relationship between the peak SNR of the reconstruction image and \( \sigma \) (namely, the signal power to background power ratio) for the three GI lidar systems is also presented, and the results accord with the curve of \( \text{SNR} - \sigma \).

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1. INTRODUCTION

Ghost imaging (GI) is a novel non-scanning imaging method to obtain a target's image with a single-pixel bucket detector [1–6]. Due to its capacity for high detection sensitivity, GI has aroused increasing interest in remote sensing, and a new imaging lidar system called GI lidar has gradually developed [7–15]. Up to now, there have been three types of three-dimensional GI lidars, namely narrow pulsed GI lidar, heterodyne GI lidar, and pulse-compression GI lidar via coherent detection [12–15]. Due to their distinct mechanisms, their advantages and disadvantages are obviously different. For narrow pulsed GI lidar, a series of high-power laser pulses with independent speckle configurations illuminate onto the target, and the backscattered intensity is directly received by a time-resolved bucket detector [7–13]. The structure of pulsed GI lidar is simple, but its imaging quality is subject to a low-detection signal-to-noise ratio (SNR). Heterodyne GI lidar employs a spatiotemporal modulated light generated by temporal chirped amplitude modulation (chirped-AM) and transverse random modulation [14]. Using a de-chirping method, a high-range resolution can be obtained even with the use of a long pulse. However, similar to narrow pulsed GI lidar, heterodyne GI lidar uses a direct light-detection mechanism, which leads to a shorter detection distance because the laser's power is relatively low compared with narrow pulsed GI lidar. Pulse-compression GI lidar via coherent detection shares similar spatiotemporal light with heterodyne GI lidar, but its detection mechanism is based on coherent detection [15]. Pulse compression gives this lidar high-range resolution, long detection range, and insensitivity to stray light. However, in order to ensure heterodyne efficiency, the laser's line width is usually very narrow and the numerical aperture of the receiving system should be very small. In remote-sensing GI lidar detection applications, background light is inevitable and its intensity may be greater than the intensity of the signal. Therefore, it would be very useful to clarify the influence of background light on the imaging quality of GI lidar systems.

In this paper, the performance of the three aforementioned GI lidar systems is analyzed in a background light environment. In Section 2, we theoretically analyze the imaging SNR of pulsed GI lidar, heterodyne GI lidar, and pulse-compression GI lidar via coherent detection, when the signal light is contaminated by background light. Following the analysis, we give a numerical simulation to demonstrate the performance of these systems under different levels of background light in Section 3. Finally, a conclusion is made in Section 4.

2. SYSTEM ANALYSIS

Figure 1 is the schematic of the three different types of GI lidar: (A) narrow pulsed GI lidar, (B) heterodyne GI lidar, and (C) pulse-compression GI lidar via coherent detection. In these lidar systems, modulated light pulses are generated and divided into reference and test paths by a beam splitter (BS). In the reference path, the light's far-field intensity distribution...
\(G_i(x_i) = \langle \delta I_i \delta I_i(x_i) \rangle\),

where \(\{\}\) is an average over independent speckle configurations, \(\delta I = I_i - \langle I_i \rangle\), and \(\delta I_i(x_i) = I_i(x_i) - \langle I_i(x_i) \rangle\). The noise associated with \(G_i(x_i)\) is \([4, 5]\)
detection mechanisms, we will analyze their detection output and image SNR. For simplicity, the conversion factor of the photoelectric detector used in the three lidar systems is assumed to be identical, and thus is ignored in the following analysis.

A. Lidar System (A)

For lidar scheme (A), a time-resolved bucket detector is used to collect the backscattered light. Since the background light’s coherence time $\tau_{bg}$ is much shorter than the detector’s integration time, if we ignore the time delay of propagation, the output can be denoted as

$$ I_A = \int_0^{T_A} dt \int_{A_{beam}} dx_t [E_t(x_{sp}, t)]^2 + |E_{bg}(x_{sp}, t)|^2 ]O(x_t). $$

$$ \approx I_{A_t} + I_{A_bg}. $$

(7)

where $O(x_t)$ is the intensity reflection coefficient of the target, and $A_{beam}$ is the area of the light beam. By substituting Eq. (7) into Eq. (2), we get

$$ \langle G_A(x_t) \rangle = T_A A_{coh,r} \langle I_r \rangle O. $$

(8)

Since $I_{A_t}$ and $I_{A_bg}$ are independent of each other, by substituting Eq. (7) into Eq. (2), we get

$$ \langle \Delta G_A^2 \rangle = \langle (\delta I_{A_t}^2) \delta I_{A_t}^2 \rangle + \langle (\delta I_{A_bg}^2) \delta I_{A_bg}^2 \rangle $$

$$ = \langle \delta I_{A_t}^2 \rangle \langle \delta I_{A_t}^2 \rangle + \langle \delta I_{A_bg}^2 \rangle \langle \delta I_{A_bg}^2 \rangle $$

$$ = T_A^2 A_{beam} A_{coh,r} \langle I_r \rangle^2 O^2 \left( 1 + \frac{\tau_{bg}}{T_A} A_{coh,r} \frac{1}{\sigma^2} \right), $$

(9)

where $\langle \delta I_{A_t}^2 \rangle \delta I_{A_t}^2 - \langle \delta I_{A_t} \rangle^2 \langle \delta I_{A_t}^2 \rangle$ is the inherent noise for GI without detection noise [16], and $O^2 = \int (I_t)O^2(x_t)dx_t/\int (I_t)dx_t \approx \int (I_t)O^2(x_t)dx_t/A_{beam}$ is the average quadratic reflection function of the target. If we average over $N$ independent measurements, using Eqs. (3), (8), and (9), we have

$$ SNR_A = \frac{N}{N_{sp}} \left[ \frac{1}{1 + \frac{\tau_{bg}}{T_A} A_{coh,r} \frac{1}{\sigma^2}} \right] O^2. $$

(10)

where $N_{sp} = A_{beam}/A_{coh,r}$ is the number of speckles in the beam and $\Delta O_{min}$ is the minimum variation of the object reflection function to be detected.

B. Lidar System (B)

For lidar system (B), the backscattered light is converted into an intensity-modulated photocurrent $i_B(t)$. Then de-chirping is processed by mixing the photocurrent with a local chirp signal $s_L(t) = \chi_{chirp}$. After a proper bandpass filter, fast Fourier transform (FFT) is used to find the beating frequency $f_z$ and accumulate the signal energy [14]. The amplitude spectrum can be denoted as

$$ I_B(f) = \text{FFT}[i_L(t)i_B(t)] \otimes H_B(t) $$

$$ = \frac{m^2}{2} T_B \text{sinc}[T_B(f - f_z)] \text{exp}[i\phi_B] \int dx_t E_B(x_{sp}, t)^2 O(x_t) $$

$$ + \text{FFT} \left\{ s_{L}(t) \left\{ \int dx_t E_{bg}(x_{sp}, t)^2 O(x_t) \otimes H_B(t) \right\} \right\} $$

$$ \approx I_{B,f}(f) + I_{B_bg}(f), $$

(11)

where $H_B(t)$ is the impulse response function for receiving system (B), sinc$(x) = \sin(\pi x)/\pi x$, $\phi_B$ is a constant delay phase, and $\otimes$ denotes convolution. Similar to the process of lidar system (A), by substituting $I_B(f_z)$ into Eqs. (1) and (2), we can obtain the reconstruction image,

$$ \langle G_B(x_t) \rangle = \frac{m^2}{2} T_B A_{coh,r} \langle I_r \rangle O, $$

(12)

and the associated noise,

$$ \langle \Delta G_B^2 \rangle = \frac{m^2}{4} T_B^2 A_{coh,r} A_{beam} \langle I_r \rangle^2 O^2 \left( 1 + 2 \frac{\tau_{bg}}{m^2 T_B A_{coh,r}} \frac{1}{\sigma^2} \right). $$

(13)

Therefore, by substituting Eqs. (12) and (13) into Eq. (3), and averaging over $N$ measurements, we can obtain the image SNR for lidar system (B) as

$$ SNR_B = \frac{N}{N_{sp}} \left[ \frac{1 + \frac{\tau_{bg}}{m^2 T_B A_{coh,r}} \frac{1}{\sigma^2}} \right] O^2. $$

(14)

C. Lidar System (C)

In lidar system (C), the light signal is mixed with the local chirped-AM modulated light $E_{LO}(t) = [1 + m_{chirp}(t)] A_{LO} \text{exp}[i\phi_{LO}]$, and the range delay signal is converted to a beating frequency $f_z$. Then FFT is applied to find the beating frequency, and a random sparse point detector array is used as an equivalent bucket detector. Finally, the intensity spectrum can be denoted as [15]

$$ I_C(f_z) = \sum \frac{m^2}{4} T_C^2 A_{LO} I_L(x_t) + \sum |i_{C_bg}(x_{sp}, f_z)|^2 $$

$$ + 2 \text{Re} \left\{ \sum m^2 |I_L| T_C \text{exp} \left[ i\phi_C \right] E_t(x_t) \right\} i_{C_bg}(x_{sp}, f_z) \right\} $$

$$ \approx I_{C,f}(f_z) + I_{C_bg}(f_z) + I_{C_C}(f_z), $$

(15)

where $I_L = |E_{LO}|^2$, $\phi_C$ is a constant phase, and $i_{C_bg}(x_{sp}, f_z)$ is the spectrum of background light output. Similar to lidar system (B), the image is retrieved by correlating $I_C(f_z)$ with the reference speckle configurations. By substituting Eq. (15) into Eqs. (1) and (2) respectively, we can obtain

$$ \langle G_C(x_t) \rangle = \frac{m^2}{4} I_L T_C^2 A_{coh,r} \langle I_r \rangle O $$

(16)
\[
\langle \Delta G^2 \rangle_C = \frac{m^8}{16} P_{LO} T_C^4 A_{\text{beam}} A_{\text{coh}}, \frac{1}{64} \langle I_\text{coh}^2 (I_e^2) \rangle \frac{1}{2} \sigma^2
\]
\[
\times \left[ 1 + \frac{64(2 + m^2)^2 (\sigma_{bg} / T_C)^2 A_{\text{coh},bg} \frac{1}{2 A_{\text{coh}} \sigma^2} \right] \frac{1}{2} \sigma^2.
\]

(17)

Thus, the SNR for lidar system (C) is

\[
\text{SNR}_C = \frac{N}{N_{sp}} \left( 1 + \frac{64(2 + m^2)^2 (\sigma_{bg} / T_C)^2 A_{\text{coh},bg} \frac{1}{2 A_{\text{coh}} \sigma^2} \right] \frac{1}{2} \sigma^2.
\]

(18)

As shown by Eqs. (10), (14), and (18), the three lidar systems have different responses to signal and background light, thus leading to different image SNRs when the three systems share the same signal power to background power ratio \( \sigma \). We will compare them explicitly in the next section.

### 3. NUMERICAL SIMULATION

In order to demonstrate the performance of these three GI lidar systems under background light, a numerical simulation is performed. The pulse duration for lidar (A) is \( T_d = 1 \) ns, and the chirped modulation parameters are \( T_{\text{chip}} = 400 \) \( \mu \)s and \( B_{\text{chip}} = 1 \) GHz; thus, the range resolutions are identical for the three lidar systems. The specific parameters for transverse modulation are also identical for the three systems, namely \( \lambda = 1550 \) nm, \( D_s = 2 \) mm, and \( f_s = 250 \) mm. For simplicity, we only simulate a single static planar target with letters “GI” (the transverse size is about 3 m x 3 m) at range \( z = 200 \) m. The measurement number is \( N = 10000 \). A random sparse detector array with 25 point detectors is used for lidar systems (A)–(C).

Figure 2 is the reconstruction images with different levels of average signal power to background power ratio. The signal power to background power ratio \( \sigma \) is -40, -30, -20, -10, 0, and 10 dB for columns (1)–(6), respectively, and rows (A)–(C) correspond to lidar systems (A)–(C), respectively. As \( \sigma \) becomes weaker, the image quality for every lidar decays. For lidar (A), when \( \sigma \leq 0 \) dB, it fails to reconstruct the image; for lidar (B), the reconstructed image is satisfactory when \( \sigma = -20 \) dB. Lidar (C) can still reconstruct the image when \( \sigma = -30 \) dB. Among the three systems, therefore, lidar (C) has the best anti-background-light performance.

![Fig. 2. Image reconstruction results. The signal power to background power ratio \( \sigma \) for columns (1)–(6) is -40, -30, -20, -10, 0, and 10 dB, respectively, and rows (A)–(C) correspond to lidar systems (A)–(C), respectively.](image)

Figure 3 gives the normalized SNR \( \text{SNR}_i / [N(\sigma_{\text{min}})]^2 \) for lidar systems (A)–(C). The theoretical behaviors [Eqs. (10), (14), and (18)] are indicated by three solid lines, while the numerical results (dashed lines) for lidar systems (A)–(C) come from the simulation results, while theoretical behaviors [Eqs. (10), (14), and (18)] are indicated by three solid lines.

Finally, to evaluate the quality of images reconstructed by the three lidar systems, the reconstruction fidelity is estimated by calculating the peak SNR (PSNR) [20]:

\[
\text{PSNR}_i = 10 \times \log_{10} \left[ \frac{(2^p - 1)^2}{\text{MSE}_i} \right].
\]

(19)

Here, the bigger the PSNR value, the better the quality of the reconstructed image. In Eq. (19), \( p = 8 \) for a 0–255

![Fig. 4. Comparison among PSNR for lidar systems (A)–(C).](image)
gray-scale image, and MSE is mean square error of the reconstruction image \( \langle G_i \rangle \) with respect to the original target \( O \), namely

\[
\text{MSE}_i = \frac{1}{N_{\text{pixel}}} \sum_{m,n} |\langle G_i(m,n) \rangle - O(m,n)|^2,
\]

where \( N_{\text{pixel}} \) is the pixel number of the reconstructed image. Figure 4 gives the PSNR curve for lidar systems (A)–(C). It is obviously seen that all curves increase with \( \sigma \), and their anti-background performance is \( (A) < (B) < (C) \). This result is consistent with the curve of SNR-\( \sigma \) in Fig. 3.

4. CONCLUSION

In conclusion, we have analyzed image SNR for (A) narrow pulsed GI lidar, (B) heterodyne GI lidar, and (C) pulse-compression GI lidar via coherent detection in the presence of background light. Our theoretical and numerical results demonstrate that narrow pulsed GI lidar fails to reconstruct images when the power of the signal light is overwhelmed by background light, while heterodyne detection GI lidar and pulse-compression GI lidar via coherent detection can still reconstruct images with a long-duration pulse. Of the three GI lidar systems, pulse-compression GI lidar via coherent detection has the best anti-background-light performance.

Since the architecture of the pulsed GI lidar system is much simpler, it is a better choice when detection SNR is high, such as in short-distance imaging applications. Backscattered signal light becomes weaker and background light is inevitable as detection distance increases; thus, pulse-compression GI lidar via coherent detection is better for remote-sensing applications.

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**REFERENCES**