

A computer vision-based approach for lunar laser ranging signal detection

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Abstract: Lunar laser ranging represents the forefront of laser ranging technology. The considerable distance to the Moon and strong background light mean that the signal-to-noise ratio of lunar laser ranging signals is much lower compared with that of satellite laser ranging signals in Earth's orbit. Accurate processing of lunar laser ranging data is essential for its scientific applications. This paper addresses the challenge of the low signal-to-noise ratio in lunar laser ranging signals by developing a detection model based on computer vision techniques. The model was tested using both simulated data with a signal-to-noise ratio as low as -19 dB and measured data as low as -12.9 dB, with the results demonstrating that the model provides reliable detection in both cases, offering a robust approach for the effective processing of lunar laser ranging data.

Keywords: Lunar laser ranging; Signal detection; Computer vision; Random sampling; Low signal-to-noise ratio signals

1. INTRODUCTION

Laser ranging technology is among the most precise methods available for detecting objects in space^[1], with Lunar Laser Ranging (LLR) presenting a major challenge, because of several key factors: The average distance between the Earth and the Moon is approximately 380 000 km, which is an order of magnitude greater than the distance for typical satellite laser ranging^[2]; the Moon's surface experiences significant background noise, mainly caused by the reflection of sunlight, with the reflected light intensity roughly equivalent to that of a 100 W light bulb^[3]; and, owing to the long distance, the telescope needs to achieve extremely high tracking accuracy to ensure that the laser precisely hits the lunar target (corner reflector)^[4,5]. These difficulties result in weak signals and strong background noise. To achieve effective LLR, the laser pulse energy and divergence angle, the telescope's

pointing accuracy, and the telescope aperture all need to meet high standards, without which, LLR would be extremely challenging.

During the process of LLR, the low signal-to-noise ratio (SNR) of the ranging data is one of the main challenges, particularly in the pointing adjustments during the ranging and the data processing after the measurement. During the ranging process, the lunar target is invisible to conventional cameras and can only be initially locked onto by adjusting the telescope's pointing, based on the lunar surface's topographical features. Given the target's near-zero visibility, fine adjustments to the telescope's pointing are typically made using a strategy that combines random pointing deviations with real-time signal strength changes. If a signal appears or strengthens at a particular deviation, it suggests that the correct pointing is likely near that deviation. However, the Moon's low SNR means that signal strength variations are not readily apparent,

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which makes pointing corrections for LLR more difficult. After the ranging process, when generating LLR data, the low SNR can make it difficult to determine whether a ranging signal is present, potentially leading to false positives or missed detections. Consequently, it is crucial to consider both the presence and absence of the signal, and the development of a high-accuracy signal detection model tailored to the low SNR of LLR is essential.

Computer vision is a field of study that focuses on enabling computers to “see” and “understand” the content of digital images and videos^[6]. It involves the development of algorithms and models that allow computers to extract, process, and interpret useful information from images or videos, ultimately enabling them to perceive the real world. Thanks to advances in machine learning and deep learning, particularly with the use of Convolutional Neural Networks (CNNs), computer vision has made pioneering progress in image recognition and understanding, becoming increasingly integrated into daily life and industrial applications^[7,8]. Driven by sufficiently large datasets, computer vision systems achieve high accuracy and consistency, performing tasks with high precision without being affected by fatigue, emotions, or distractions^[9].

The You Only Look Once (YOLO) series is one of the best-known object detection models in the field of computer vision, widely acknowledged for its efficient, real-time performance^[10]. Based on CNNs, the YOLO model extracts features from images, continuously adjusting the network weights during training and ultimately performing inference to complete the optimization process. Its core advantage lies in its ability to detect multiple objects within an image in real-time, providing both their locations and categories. YOLOv8 is a version proposed by Ultralytics in 2023, which incorporates a more advanced backbone and neck architecture, designed to further enhance the performance and efficiency of target detection.

Li et al.^[11] proposed a method based on binary images to process laser ranging data. They first mapped the raw data into binary images, and using the density distribution of the laser ranging data, performed filtering and signal extraction. Finally, they reverse-mapped the processed binary image to obtain the signal data, enabling signal extraction through the shape characteristics of the signal. However, they did not fully utilize the advantages of image processing, as for data with varying echo intensities, manual adjustment of parameters was still required. Feng et al.^[12] introduced deep learning models into signal extraction from laser ranging data, successfully using deep learning techniques to extract target signals with relatively good results. However, they did not address the issue of low SNR conditions. Xue et al.^[13] employed DeepLabCut, an automatic annotation method primarily used for motion tracking and posture estimation, to process the laser ranging data. However, the results showed that the key points obtained through this method experienced drift, misalignment, and uneven distribution, leading to suboptimal performance. Therefore, further research

is needed on signal extraction methods for laser ranging data with low SNR, to improve the effectiveness of signal extraction tasks in low SNR data.

Whether data contains a signal is a prerequisite for performing signal extraction tasks and other related work^[14,15]. In this study, we focus on LLR data and attempt to establish a high-accuracy signal detection model suitable for the low SNR of LLR^[16]. We apply this model to the measured data from the TianQin Project laser ranging station (hereafter referred to as the TianQin Station), to evaluate its performance.

2. MODEL AND DATA

2.1. Laser Ranging Data

The principle behind laser ranging involves emitting laser pulses from a laser ranging station toward a target. By recording the epochs at which these pulses leave and return to the station, the round-trip time of the pulse allows the distance between the station and the target to be calculated. Each laser pulse corresponds to a single measurement, with each measurement yielding multiple results, some containing noise and others containing the actual signal. When integrating the data from a single measurement period, the distribution of the ranging signal tends to be concentrated and orderly, while the distribution of noise is scattered and disordered.

Given that most targets in laser ranging are moving, the measurement results are commonly represented by the residuals between the measured values and the predicted results. Consolidated laser ranging Prediction Format (CPF) is a standard prediction format for laser ranging, defined by the International Laser Ranging Service (ILRS). A CPF file for a particular space-based target records its geocentric coordinates at a specific time. Prediction files used in laser ranging can be derived from the CPF file using coordinate transformation, and by matching the original data with the prediction, the residuals of the laser ranging data can be obtained.

The laser ranging data format consists of several pairs of numbers (t, r) , where t is the epoch the laser pulse leaves the station, and r is the corresponding residual value. When the prediction is accurate, the residuals of the ranging signal are typically concentrated along a straight line with a slope near zero. The number of signals and noise varies considerably depending on the SNR, which can be calculated as

$$SNR = 10 \cdot \log \frac{N_{\text{signal}}}{N_{\text{noise}}}, \quad (1)$$

where N_{signal} and N_{noise} are the number of signal data points and the number of noise data points, respectively, within the selected region.

2.2. Signal Detection Model

With the development of deep learning and related

algorithms, many different models have emerged in the field of computer vision, each designed for specific tasks and application scenarios. Image classification is one of the most fundamental and important tasks in computer vision, aiming to assign one or more predefined category labels to an input image^[17].

LLR signals are scattered around the error margins of the laser ranging station system, with most of the points approximately forming a straight line. If LLR data are converted into image data, the problem of detecting the ranging signals, computer vision is well-suited to address this challenge. Laser ranging signal data can be seen as one or more segments of local curve targets, which aligns well with the characteristics of the YOLO series. This paper uses YOLOv8 as the signal detection model, categorizing the ranging data into classes of “signal present” and “signal absent”.

To train YOLOv8, the dataset should be split into three distinct subsets (Train, Val, and Test) to ensure the model generalizes well to new data. The Train subset is used to teach the model, which learns features and adjusts its weights by processing this data repeatedly during training. Validation (Val) is used during training to monitor performance on unseen data. It helps tune hyperparameters and prevents overfitting by providing an unbiased evaluation after each epoch. Finally, the Test subset is used after training is complete, to provide a final, “real-world” assessment of the model’s accuracy. These data should never be seen by the model during the learning phase.

2.3. Dataset Construction

The TianQin Station is located in Guangdong Province, China. It began operation in 2019, and in the same year, it successfully measured all five lunar surface corner reflectors^[18,19]. The key parameters of TianQin Station include 300 mJ pulse energy, 80 ps pulse width, 1064 nm wavelength, 1.2 m telescope aperture, and 1" tracking accuracy.

Fig. 1 shows the residual data of the LLR from the TianQin Station. The figure clearly illustrates that there is a significant amount of noise in LLR. To ensure consistency in processing, the residual plots are divided based on a duration of 300 s and a residual range of 300 ns, saved as 640×640 pixel red, green, and blue (RGB) images, where the mark of each data point is a 10 pt blue solid dot, as shown in Fig. 2. These parameters can be adjusted according to actual conditions. Because there are relatively few valid echo photons in LLR, we choose a duration of 300 s and a residual range of 300 ns to ensure sufficient echo signals. For the horizontal axis, a shorter duration may lead to information loss, while a longer duration may introduce environmental effects. For the vertical axis, a larger residual range would increase the error in signal extraction, while a smaller residual range would reduce the extraction error, but the smaller range might result in the loss of some features used for detection. By

dividing the ranging data into small parts, the stability of the SNR can be maintained over short time intervals. This can reduce the impact of non-stationary conditions, and the difficulty of accumulating training dataset.

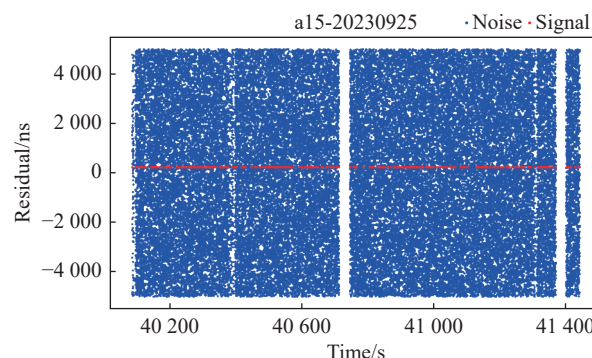


Fig. 1. Plot of LLR residuals.

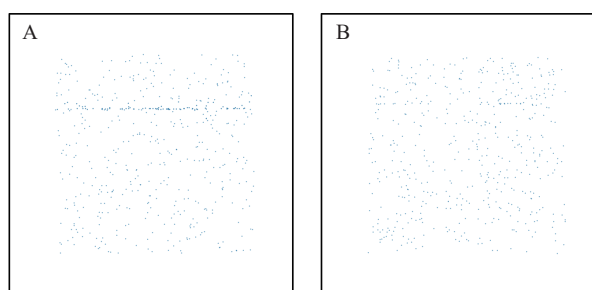


Fig. 2. Constructed data with different SNR. (A) High SNR, showing the true signal as a distinct straight line. (B) Low SNR, showing the true signal as several adjacent datapoints. The mark of each data point is a 10 pt blue solid dot.

In LLR, the actual signal obtained from the ranging measurements is relatively low, and the SNR of the ranging data is determined by both the system and the background. To increase the amount of effective signal data and enhance the model’s generalization ability under different SNR conditions, we construct LLR residual data with different SNRs using random sampling from the existing LLR residual data.

In the sampling method, the residual data points are first classified into signal and noise sets using conventional methods such as histogram and polynomial fitting. The required quantity of signal and noise is then calculated, based on the desired SNR. Finally, the specified SNR dataset is constructed by selecting the specified quantity of data from the signal and noise sets.

It is important to ensure that the number of signals in the signal set is sufficient to enable the model to learn effective features during the construction of simulated data. Fig. 2 shows the data for different SNRs. To enhance the model’s robustness and generalizability, it is necessary to enrich the data sample where signal points are located in different position by changing the starting position.

Fig. 2A and Fig. 2B are both simulation samples based on measured data in TianQin Station. There is a

difference in SNR between simulations. Fig. 2A has a high SNR, with most points concentrated on a horizontal line and fewer scattered points. In contrast, Fig. 2B has a low SNR where, in addition to the points concentrated along a horizontal line, there are also many scattered points distributed elsewhere. Once the dataset is constructed, it is randomly split into training, testing, and validation sets according to a specified ratio (e.g., 5:3:2), after which model training can begin. The training process itself is complex, including various stages such as feature learning, logical reasoning, and other detailed procedures, but modern deep learning toolkits provide a streamlined choice for configuring all relevant settings with minimal effort (such as inputting the epoch and image size). We use the YOLOv8 training model to train our detection model.

3. MODEL RESULTS

Based on LLR data from TianQin Station, we created a dataset comprising 17160 samples. The training set contains 9453 of the samples (55%), the validation set contains 4649 samples (27%), and the test set contains 3058 samples (18%). The test set is composed of LLR data from different days to the training and validation sets.

The SNR range for the training and test sets is between -8 dB and -13 dB, while the SNR range for the test set is between -9 dB and -19 dB.

We trained the YOLOv8 model (incorporating 10 layers, with 1440850 parameters) on this dataset using a single GPU with 24 GB of memory and 16384 Compute Unified Device Architecture cores. When performing prediction tasks, the model can output results in approximately 1 ms. The confusion matrix for the test results is shown in Fig. 3A. The trained model classified all 2941 noise samples as noise and 117 signal samples as signals, correctly completing all detections.

To provide a clearer demonstration of the model's detection results, Fig. 3B shows the relationship between SNR and average probability by averaging the probability values of signals at different SNR levels in the validation set. As the SNR decreases, the average probability tends to drop. However, at -19 dB, there is a slight increase in average probability, which may be due to certain features in the simulated data being captured by the model, allowing it to give a stronger probability judgment that the data correspond to a signal. Similarly, at a SNR of -9 dB, the model is likely to give a lower probability because the features of the simulated data may have been compromised.

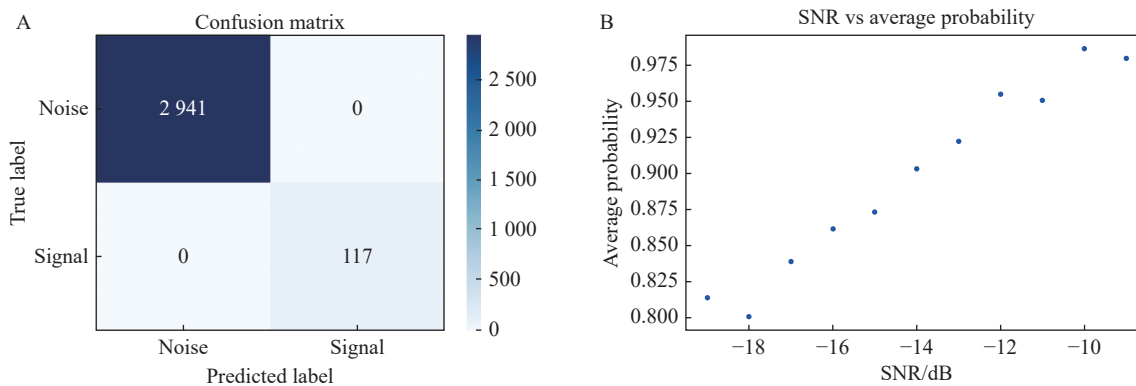


Fig. 3. Quantitative metrics for the detection model. (A) Confusion matrix. The numbers in the top-left and bottom-right cells show the number of correctly classified items, while the other two cells give classification errors. (B) Relationship between SNR and average probability, showing a directly proportional increase.

Feature visualization techniques are important tools in modern deep learning, used to ascertain how a deep learning model works, being effectively like a camera placed inside the model. We inputted one image (Fig. 2B), where the signal points are located in the upper right portion, into the model, extracted the output from the last convolutional layer, and visualized its top 32 features. The areas with the highest values in the heatmap closely correspond to the locations of signal points in the input image (see Fig. 4).

Overall, the results from training and validation of the model, using simulated data, were quite promising. This confirms the feasibility of the LLR signal detection model.

4. EXPERIMENTAL VERIFICATION

Apart from the low SNR data, from numerical simulations, it is also possible to artificially create conditions with even lower SNR, to further validate the model. This section discusses several methods for generating such low SNR conditions. Because these low SNR conditions are artificially generated, we assume that the data do indeed contain ranging signals.

4.1. Experimental Setup

There are several ways to reduce the SNR of the measured signal, with one being reducing the sensitivity

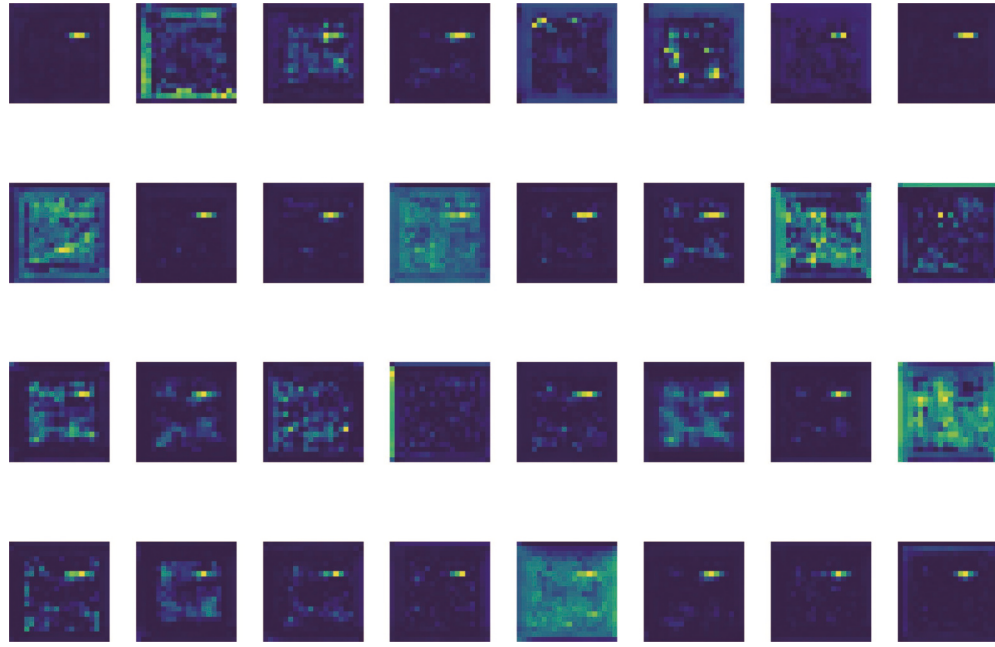


Fig. 4. Results for the top 32 features in the last convolutional layer. The brightness of the colors show the weight of the classification features, with brighter colors indicating more prominent features. In each case, there is a bright area in the upper right corner, which corresponds to the location of the ranging signal.

of the photodetector. The superconducting single-photon detector used at TianQin Station allows for adjustment of the detector's sensitivity by changing the operating current. Lowering the sensitivity reduces the likelihood of detecting photons, which decreases both the signal and noise levels. When the signal is strong, this method can help reduce the SNR of the ranging data to some extent.

Another method is to adjust the position of the secondary mirror to defocus the optical system. Defocusing the secondary mirror causes the light to not converge properly at the focal point, increasing the divergence angle of the laser pulse during emission and reception. This, in turn, reduces the strength of the returned signal. The impact on randomly occurring noise is limited. This method can also slightly increase the optical path length within the ranging station, causing a shift in the signal's position.

Finally, SNR can be reduced by adjusting the telescope's pointing. A small pointing adjustment can cause the distribution of the strongest energy to shift away from the target, instead measuring lower-energy parts of the signal. This directly reduces the number of returned photons, lowering the SNR of the ranging data. However, in LLR, because a change in angle leads to a large shift in the spot position, selecting an appropriate off-target amount can be challenging.

Provided that the signal from the target is measured, these methods can be used to reduce the SNR of the signal to some extent.

4.2. Method Validation

In LLR, system calibration is a vital step to ensure the accuracy and reliability of the measurements. This involves adjusting the measurement equipment using

known reference standards to correct any inherent biases or errors. Ground-based target measurements are commonly used for system calibration in laser ranging. Fig. 5A shows the results measured after defocusing, while Fig. 5B presents the results measured after focusing.

After adjusting the focal length, the signal strength from the ground-based target significantly decreases. The echo signal counts from the four channels change from [12082, 2326, 12117, 12244] to [785, 183, 947, 681]. Additionally, the position of the signal shifts, increasing by approximately 0.5 ns. Therefore, adjusting the focal length of the optical system can alter the signal strength.

4.3. Experimental Results

The low SNR data obtained using the methods outlined in Section 4.1 are shown in Fig. 6. The SNR values range from -14.8 dB to -5.2 dB. The red points in Fig. 6 are examined in greater detail in the corresponding image in Fig. 7.

It is worth noting that the signal counts in Fig. 7A, Fig. 7D, Fig. 7E, and Fig. 7F are 14, 28, 31, and 38, respectively, while Fig. 7B and Fig. 7C have 84 and 101 signals. The signal density is quantified using information entropy H , which can be calculated as

$$H = - \sum_{i=1}^n p_i \cdot \ln p_i, \quad (2)$$

where p_i is the proportion of points within each grid cell after grid division relative to the total number of points. During grid division, each dataset is divided into small groups, each spanning 25 s along the horizontal axis, with no additional segmentation along the vertical axis. The

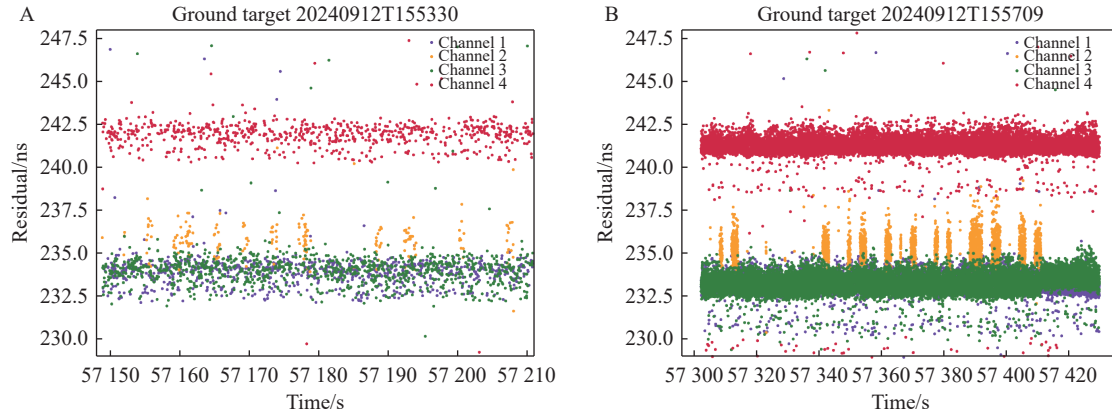


Fig. 5. Results of ground target measurements with adjusted focal length, showing that when the laser ranging system is defocused, there is a significant decrease in the number of signal points. (A) Defocused. (B) Focused.

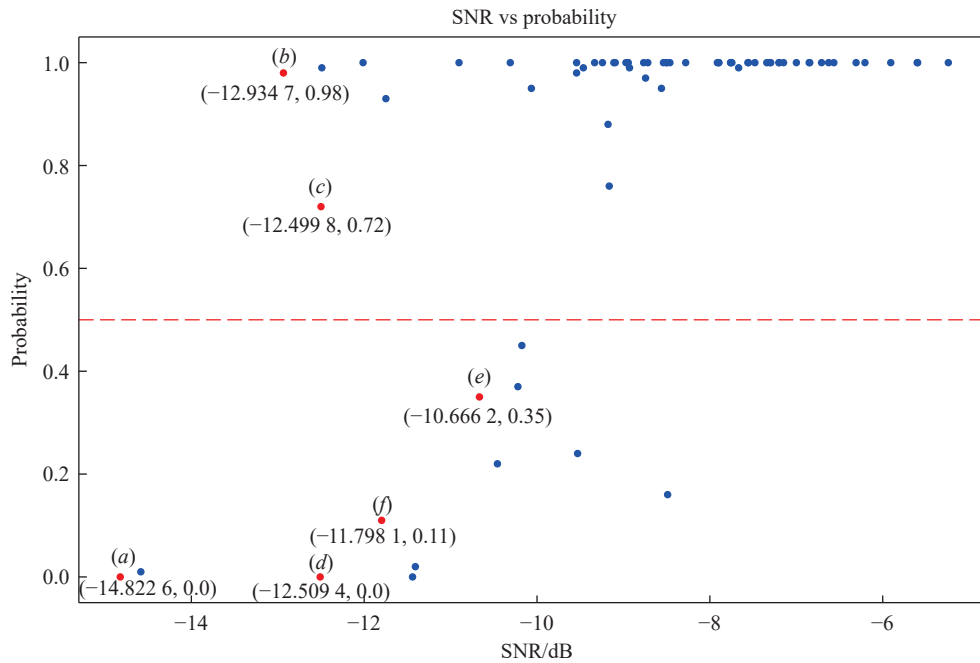


Fig. 6. A plot of SNR vs probability for measured data. Each point corresponds to the probability obtained after feeding an image into the model. The red dashed line shows a probability of 0.5.

information entropy values for Fig. 7A, Fig. 7D, Fig. 7E, and Fig. 7F are 1.71, 1.99, 2.07, and 2.01, respectively, while for Fig. 7B and Fig. 7C, the information entropy values are 2.19 and 2.14. There is a relationship between the number of signals, the magnitude of the information entropy, and the model's detection performance, but the interpretation of YOLOv8 results remains a challenging task that requires further analysis.

After attempting to combine different features and propose an equation for the parameters. Features worth considering include signal position, degree of dispersion, block density, and SNR. We can characterize these quantities using the mean residual score, standard deviation of residual scores, information entropy, and total points respectively. The parameter can be defined to establish a link between digital features and the probability of the pres-

ence of actual signals. These follow the relation

$$X = |M| \cdot H \cdot L \cdot \exp[5 \cdot L / (N - L)] / S, \quad (3)$$

where M is the absolute value of average of the residuals of all the points being counted, H is the information entropy, L is the maximum number in histogram statistics, N is the total points and S is the standard deviation of all the points being counted. For data in which signals cannot be clearly identified, reference can be made to historical ranging data, to determine potential signal positions. Data points falling within these positions are considered potential signals to calculate SNR.

Taking X as the horizontal coordinate, the probability given by the model as the vertical coordinate can be obtained in Fig. 8. When the value of X is greater than 1.2, the probability is very close to 1, so it is not shown

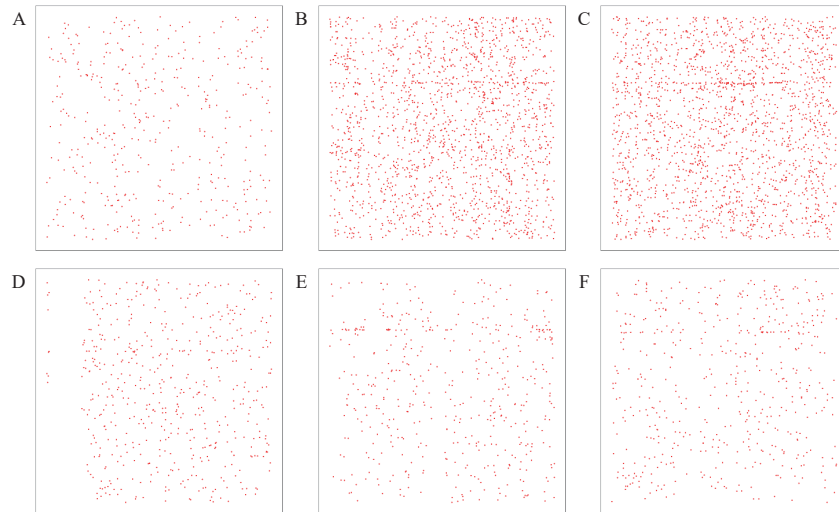


Fig. 7. Detailed images of low SNR data. To calculate the SNR, the maximum value of the histogram statistics in each dataset is set to the number of signals. Remaining points are treated as noise. (A) -14.82 dB. (B) -12.93 dB. (C) -12.50 dB. (D) -12.51 dB. (E) -10.67 dB. (F) -11.80 dB.

in the Fig. 8. When the parameter X is low, the probability of the presence of a signal is also relatively low. However, when X is high, the probability of the presence of a signal increases significantly. This suggests that the parameter X can be used as an indicator, to initially determine whether a signal exists or not. The red curve in Fig. 8 shows the expected curve, but many points lie far from this. Consequently, it is still difficult to achieve accurate signal description and identification based on parameter X alone, and X can be regarded as an empirical value that still requires improvement. This also confirms the value of the model in this paper. We should emphasize that Equation (3) is not a perfect physical equation, but is simply an approximation.

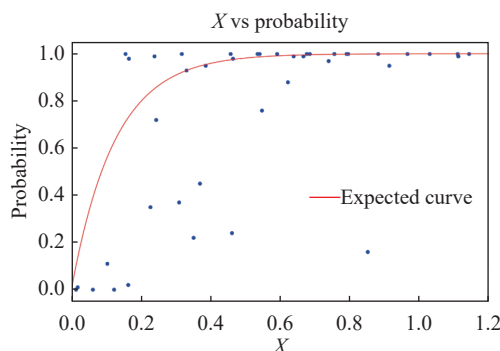


Fig. 8. A plot of parameter X against probability. The blue dots show experimental results of the model, while the red curve shows the predicted ideal outcome. When the probability is over 0.8, the experimental results align closely with the prediction; however, when the probability falls between 0.1 and 0.5, the alignment between the experimental results and the predicted outcome is weaker.

The influence of external weather conditions and internal system factors cause some potential variation in the residual data from each laser ranging measurement. With

the continued advancement of deep learning technology, the model may still be applicable to even lower SNR data. However, final verification by humans should still be used as a safeguard.

5. CONCLUSION

We have successfully developed an LLR signal detection model using a computer vision framework. After validation, the model demonstrates high accuracy. Even when the SNR of the simulated data falls to -19 dB, the model still maintains 100% accuracy, provided the number of signal points is sufficient. In the measured data, the model can effectively identify signals when the SNR reaches -12.9 dB. These results suggest that the computer vision model can support research on LLR data under low SNR conditions. In this study, we did not explore the adaptability of other deep learning models, and there may be models that can perform better. With the continued advancement of deep learning and other scientific technologies, it is likely that the limits for LLR signal detection will be further extended. Additionally, because LLR data are influenced by various factors and are highly diverse, expanding the dataset to include more ranging data from different conditions could enhance the model's generalizability.

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AI DISCLOSURE STATEMENT

DeepSeek was employed for language and grammar checks within the article. The authors carefully reviewed, edited, and revised the DeepSeek-generated text to their

own preferences, assuming ultimate responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Chengkai Zhou conceived the ideas, designed and implemented the study, and wrote the paper. Hui Li performed the statistical analysis. Han Yao revised the paper. Ning Xu and Xida Han provided hardware maintenance. Xianlin Wu collected the data. Xudong Lin and Ming Li provided guidance and oversight for the research. Hongchao Zhao managed and coordinated the research. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

Ming Li is an editorial board member for *Astronomical Techniques and Instruments* and was not involved in the editorial review or the decision to publish this article. The authors declare no competing interests.

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