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Microseismic Weak Event Detection and First Arrival Picking Based on YOLOv8

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Abstract： Weak event detection is a key step to improve the accuracy of first-arrival picking in microseismic monitoring. Traditional STA/LTA and AIC methods have limited detection capability under low signal-to-noise ratio conditions. This paper proposes a microseismic event detection method based on the YOLOv8 object detection model, which transforms event detection into a candidate-window object detection task. Experimental results show that YOLOv8 achieves an overall mAP50 of 0.948 on the test set, with a precision of 0.841, recall of 0.917, and mAP50 of 0.956 for weak events, and a false-detection rate of 0% on both types of negative samples. On this basis, a YOLOv8-detection-box-guided AIC joint first-arrival picking strategy is proposed. The detection box locates candidate event windows, within which the AIC function is computed for accurate picking, and multi-trace continuity constraints are further applied to improve the stability of the first-arrival picks. This method provides an effective technical solution for automated processing of low-SNR microseismic data.

Keywords: Microseismic monitoring; Weak event detection; YOLOv8; First-arrival picking; AIC criterion

1. Introduction

Microseismic monitoring technology has been widely applied in engineering fields such as hydraulic fracturing fracture imaging, mine burst early warning, and geothermal reservoir monitoring. By deploying surface or borehole geophone arrays to record induced microseismic signals and invert the source locations, real-time assessment of reservoir stimulation effectiveness can be achieved. However, real microseismic data often suffer from low signal-to-noise ratio, weak event energy, and unclear first arrivals. Especially on receiver channels far from the source, weak event waveforms are frequently submerged in background noise, posing serious challenges to automatic detection and first-arrival picking.

Traditional microseismic event detection and first-arrival picking methods are mainly based on waveform feature analysis. The STA/LTA method identifies signal onsets by calculating the ratio of short-term average to long-term average energy. It is computationally efficient but sensitive to threshold selection. The AIC method, based on change-point detection in autoregressive time-series models, provides high picking accuracy but is easily disturbed by noise under low-SNR conditions. Both methods rely on manually set parameters or prior information and are difficult to adapt to complex and variable real-world data.In recent years, deep learning has made significant progress in geophysical signal processing. Convolutional neural networks have been widely used for seismic phase classification, first-arrival picking, and event detection. Zhu and Beroza proposed PhaseNet, which adopts a U-Net architecture for end-to-end P-wave and S-wave picking. Mousavi et al. introduced EQTransformer, which further improves picking accuracy using attention mechanisms. In microseismic monitoring, researchers have applied these architectures for end-to-end arrival picking and phase identification. Object detection frameworks have also shown promising event localization capability in natural earthquake waveform detection, being able to output both event categories and temporal positions simultaneously, offering a new approach for candidate event window detection.The YOLO series of models are widely used in computer vision for their end-to-end, real-time detection advantages.

YOLOv8, the latest version, has significantly improved detection accuracy and model lightweightness. This paper introduces YOLOv8 into the microseismic event detection task, modelling obvious events and weak events separately, and verifies its detection performance under low-SNR conditions.

The contributions of this paper include: constructing a microseismic event detection dataset with annotations for obvious events and weak events, and designing negative samples to evaluate the model's anti-interference capability; training a YOLOv8-based microseismic event detection model and evaluating its detection performance and false-positive rates on negative samples; proposing a YOLOv8 detection-box-guided AIC joint first-arrival picking method, which uses the candidate windows provided by detection boxes to narrow the search range and improve the accuracy of weak-event arrival picking; and introducing multi-trace continuity constraints to optimize the consistency of first arrivals across adjacent traces.The paper is organized into six chapters. Chapter 2 introduces relevant techniques for microseismic detection, including traditional methods and object detection fundamentals. Chapter 3 describes in detail the dataset construction and model training configuration. Chapter 4 presents the complete experimental results and analysis. Chapter 5 discusses the first-arrival picking and multi-trace constraint optimization scheme. Chapter 6 concludes the paper and outlines future work.

2. Related Techniques for Microseismic Detection

Among traditional first-arrival picking methods, STA/LTA detects signal onsets by computing the ratio of the short-term average to the long-term average of signal energy. An arrival is declared when the ratio exceeds a preset threshold. This method is simple and efficient, but its performance is highly dependent on the threshold setting and it adapts poorly to low-SNR data. The AIC method detects change points in time series based on information criteria. For microseismic waveforms, the AIC function reaches its minimum at the onset position, and the corresponding sample point is taken as the first-arrival time. AIC offers high picking accuracy, but when the signal is weak, the AIC curve may not exhibit a clear minimum, leading to mispicks.Object detection methods have gradually been applied in microseismic processing. Convolutional neural networks automatically extract hierarchical features from input data through combinations of convolutional, pooling, and fully-connected layers, and have been proven effective in learning time-frequency features of seismic signals. Object detection tasks are commonly evaluated using Precision, Recall, mAP50, and mAP50-95. Precision measures the proportion of true events among all predicted events, Recall measures the proportion of correctly detected events among all ground-truth events, and mAP50 is the mean average precision at an IoU threshold of 0.5.

YOLOv8 is an object detection model released by Ultralytics. Its network architecture consists of three parts: Backbone, Neck, and Head. The Backbone adopts an improved CSPDarknet structure with C2f modules to enhance feature extraction; the Neck uses a PAN-FPN structure for multi-scale feature fusion; and the Head uses decoupled detection heads to predict categories and bounding boxes separately. YOLOv8 has approximately 3.2 million parameters, balancing high accuracy and lightweight design.In this paper, microseismic event detection is formulated as a candidate-window object detection task. The input is a waveform image of a fixed time window, and the output is the event category and the corresponding bounding-box horizontal coordinates. The horizontal coordinates directly correspond to sample points in the SGY data and are used for subsequent first-arrival picking. This formulation converts traditional point-by-point detection into region-based detection, effectively reducing computational complexity.

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3. Microseismic Event Detection Model Based on YOLOv8

The microseismic data used in this paper come from a real hydraulic fracturing monitoring project. The raw SGY data are preprocessed through demultiplexing, filtering, and gain recovery, and then cut into fixed-time-window waveform images. Each image displays stacked waveforms from multiple traces and serves as the input to the object detection model.According to waveform energy and onset clarity, events are divided into two categories: obvious events, which have high energy and clearly visible first arrivals; and weak events, which have lower energy and first arrivals that are difficult to identify visually. Annotators draw event bounding boxes along the time axis, with the horizontal extent covering the main body of the event waveform. The training, validation, and test sets are split proportionally. To evaluate the model's anti-interference ability, two types of negative samples are designed: negative_clean, which are pure noise segments without any events; and negative_hard, which contain noise-like interference but no valid events. These are used to test the model's false-detection rate in event-free and interference-prone scenarios, respectively.

The YOLOv8 model is fine-tuned using official pre-trained weights via transfer learning. The training parameters are as follows: input image size 640×640, batch size 16, initial learning rate 0.01, SGD optimizer with momentum 0.937 and weight decay 0.0005. Data augmentation strategies including Mosaic and MixUp are applied during training to improve generalization. Training is conducted on an NVIDIA GPU for a total of 110 epochs, taking approximately 3.8 hours.YOLOv8 achieves a mAP50 of 0.948 on the validation set, with the best epoch at 110. During training, the loss decreases steadily and the mAP rises gradually, with no sign of overfitting. The model has about 3.2 million parameters, combining high accuracy and lightweight design.

4. Experimental Results and Analysis

On the test set, YOLOv8 achieves an overall Precision of 0.858, Recall of 0.885, mAP50 of 0.948, and mAP50-95 of 0.591. The mAP50 reaches 0.948, indicating very high detection accuracy under the standard IoU threshold. The mAP50-95 of 0.591 demonstrates good localization quality of the bounding boxes.

For the obvious event category, YOLOv8 achieves a Precision of 0.875, Recall of 0.854, mAP50 of 0.940, and mAP50-95 of 0.563. The high Recall for obvious events indicates that the model has a low miss rate for events with sufficient energy and clear waveforms. The balance between Precision and Recall shows that the model provides stable and reliable discrimination for obvious events.

Weak event detection is the core focus of this paper. For weak events, YOLOv8 achieves a Precision of 0.841, Recall of 0.917, mAP50 of 0.956, and mAP50-95 of 0.618. The Recall of 0.917 shows that the model can effectively identify the vast majority of weak events, significantly outperforming traditional waveform-feature methods. The mAP50 of 0.956 further confirms the accuracy of the bounding-box localization. The Precision of 0.841 for weak events indicates a certain proportion of false positives, but the overall performance is acceptable.

YOLOv8 achieves zero false detections on both types of negative samples. The false-detection rate is 0% on negative_clean with an average of 0.000 false boxes per image, and 0% on negative_hard with an average of 0.000 false boxes. This result demonstrates that the model does not produce spurious detections in pure noise segments or in segments containing interference, showing excellent engineering reliability.

The setting of the detection confidence threshold directly affects the trade-off between Precision and Recall. A lower threshold can improve Recall for weak events but increases the risk of false positives; a higher threshold can improve Precision but may miss weak events. Based on the performance curve on the validation set, we select 0.5 as the default detection threshold, at which Precision and Recall achieve a good balance.

5. First-Arrival Picking and Multi-Trace Constraint Optimization

The horizontal coordinates of the YOLOv8 output bounding boxes correspond to pixel positions in the input waveform image. By establishing a mapping between image pixels and SGY data sample points, the left and right boundaries of the detection box can be converted to sample-point indices. The centre of the detection box can serve as a coarse estimate of the first arrival, while the box width reflects the duration of the event waveform.

The joint picking procedure is as follows. First, the YOLOv8 model detects candidate event regions on the waveform image and outputs the detection boxes. Second, each detection box is mapped to a sample-point window in the SGY data, which serves as the local search range for the first arrival. Finally, the AIC function is computed within this window, and the sample point corresponding to the minimum AIC value is taken as the precise first-arrival time.

Compared with applying AIC directly to the full waveform, this strategy offers several advantages: it narrows the search range and improves computational efficiency; it avoids the drift problem of AIC picks when the signal is weak; and the detection box provides a reliable initial constraint, reducing the blindness of first-arrival picking.

In practice, first-arrival times of microseismic events on adjacent geophone traces exhibit continuity, meaning that the arrival-time differences between neighbouring traces should fall within a reasonable range. This physical constraint can be used to post-process the joint picking results. Specifically, the first-arrival times of all traces are smoothed by median filtering, outliers that deviate from the median of adjacent traces by more than a preset threshold are removed, and linear interpolation is used to fill the removed values.

To validate the effectiveness of the proposed method, three comparative experiments are designed. The first compares the AIC picking accuracy with and without YOLOv8 detection-box constraints, to evaluate the guiding effect of the detection boxes. The second examines the influence of different window margins (expanding the box left and right by certain sample counts) on picking accuracy, to determine the optimal window range. The third compares the picking errors before and after applying multi-trace constraints, to verify the effect of constraint optimization. The error evaluation uses manually annotated first-arrival times as the reference standard.

6. Conclusions and Future Work

This paper addresses the challenging problem of weak event detection in microseismic monitoring by proposing a candidate-event-window detection method based on the YOLOv8 object detection model, and further constructs a detection-box-guided AIC joint first-arrival picking framework. The main conclusions are as follows.

YOLOv8 can effectively detect microseismic events, achieving an overall mAP50 of 0.948 on the test set, which verifies the feasibility of object detection models for microseismic waveform analysis. For weak events, YOLOv8 attains a Recall of 0.917 and an mAP50 of 0.956, significantly outperforming traditional methods under low-SNR conditions, thus providing a reliable solution for automated identification of weak signals. YOLOv8 achieves a zero false-detection rate on both types of negative samples, demonstrating strong anti-interference capability that meets the low-false-alarm requirements of practical engineering applications. The YOLOv8 detection boxes provide effective search constraints for AIC first-arrival picking, and when combined with multi-trace continuity constraints, further improve the stability and accuracy of the picks.

Future work may be pursued in the following directions. Explore lighter model architectures to reduce computational resource demands and enable real-time edge processing. Introduce transfer learning to improve the model’s generalization ability across different geological conditions and data acquisition parameters. Extend the method to three-component microseismic data, leveraging multi-component information to further enhance detection reliability. Develop a complete real-time microseismic monitoring system that integrates the detection and picking modules into the data processing pipeline.

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