Claims

1. A method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution is characterized in that: It is based on the YOLOv11-OBB framework, and uses the yolo11-Hybird-obb.yaml configuration file to hybridly modify the backbone network and neck structure. The specific implementation steps are as follows:

    S1: Introducing the DynamicConv dynamic convolution module in the YOLOv11 backbone network to replace some static convolutions or C3/C2f structures, improving the adaptability and expression ability of feature extraction;

    S2: Embedding the Axiom axial large kernel feature enhancement module on the high-level feature maps of the backbone, enhancing the modeling of slender ships and complex backgrounds through multi-scale deep separable convolution, axial interaction attention, and local contrast enhancement;

    S3: Adopting the GateDySample gated dynamic upsampling module in the neck structure, performing adaptive fusion of multi-scale features in the high-resolution space through bilinear baseline, edge-preserving refinement, and global gating;

    S4: On the modified backbone network and neck structure, using the YOLOv11-OBB directional detection head to jointly predict the category, center position, major and minor axis lengths, and rotation angle of the ship target, and using the loss function adapted to SAR characteristics for end-to-end training;

    S5: After preprocessing the SAR image to be detected and inputting it into the trained model, output the detection results including directional bounding boxes and confidence levels. Performing post-processing using rotated non-maximum suppression (Rotated NMS) to obtain the directional ship detection results at sea.

2. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The implementation process of the Axiom axial large kernel feature enhancement module in step S2 is as follows:

    Based on the input feature $X \in \mathbb{R}^{C\times H\times W}$, obtaining $\tilde{X} = BN(X)$ through batch normalization;

    The multi-scale deep separable convolution branch uses different convolution kernel sizes and dilation rates for deep separable convolution, and after channel dimension fusion, it obtains the multi-scale response $Y^{ms} = f_{ms}(\tilde{X})$;

    The axial interaction branch performs average pooling along the height and width directions, and through 1×1 convolution and nonlinear transformation, generates the axial attention map A, and element-wise modulation of the input feature to obtain $Y^{ax} = \tilde{X} \odot A$;

    The local contrast enhancement branch estimates the background component through smooth convolution and constructs residual details, and through convolution sharpening initialized by Laplacian thinking, obtains the contrast-enhanced feature $Y^{ct} = f_{ct}(\tilde{X})$;

The output of the three branches is weighted fused by the learnable weights α, β, and γ satisfying $\alpha + \beta + \gamma = 1$ to obtain $Y^{fuse} = \alpha Y^{ms} + \beta Y^{ax} + \gamma Y^{ct}$;

The fused features are transformed through a channel feedforward network (FFN) composed of 1×1 convolution, and through residual connection, the module output $Y = X + FFN(Y^{fuse})$ is obtained.

3. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The DynamicConv dynamic convolution module in step S1 obtains the channel description vector through global average pooling, and generates the routing weights of multiple expert convolution kernels based on this vector, forming equivalent convolution kernels related to the input, to achieve adaptive modeling of different scales, directions, and texture patterns.

4. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The implementation process of the GateDySample gated dynamic upsampling module in step S3 is as follows:

Performing bilinear interpolation upsampling on the low-resolution feature to obtain the baseline output;

edge refinement is achieved through deep separable convolution initialized by the Laplacian idea in high-resolution space;

Scalar gated coefficients are generated from the global average pooling vector of the input features, and the "difference between the refined result and the bilinear result" is scaled and superimposed. When the gated value is close to 0, it degenerates to pure bilinear upsampling, and when it is close to 1, the edge refinement result is fully utilized.

5. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The preprocessing in step S5 includes gray normalization, speckle noise suppression, contrast enhancement, and cropping or scaling the image to a unified input size of 640×640.

6. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The training data is labeled with OBB corner coordinates for the ship target, and the target position and deflection are located by recording the coordinate sequence of the four vertices of the bounding box $(x_1, y_1, x_2, y_2, x_3, y_3, x_4, y_4)$, and the training set, validation set and test set are divided in a ratio of 7:2:1.

7. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The Axiom axial large kernel feature enhancement module in step S2 adapts to different preset types of different scale feature maps of the backbone network: in the high-resolution stage (P2/P3), it uses AxiomYOLOBlockTiny or AxiomYOLOBlockHeavy, and in the middle and high-level stage (P4/P5), it uses AxiomYOLOBlockLite or AxiomYOLOBlockMedium.

8. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The DynamicConv dynamic convolution module is mainly deployed in the middle and deep layers of the backbone network, and the standard convolution or lightweight structure is retained in the shallow stage, while enhancing the expression ability at the high semantic level while controlling the computational overhead.

9. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The hyperparameters of the training process are set as: the number of training epochs epochs=300, batch size batch=32, input size imgsz=640, the optimizer is stochastic gradient descent with momentum (SGD), the momentum coefficient momentum=0.937, the weight decay weight_decay=0.0005, the learning rate=0.01, AMP mixed precision is enabled and the early stopping strategy (patience=50) is used.

10. According to the method for oriented small ship target detection in SAR based on axial large kernels and dynamic convolution as described in Claim 1, it is characterized in that: The depth coefficient, width coefficient and the repetition times of each module in yolo11-Hybird-obb.yaml can be adjusted to trim the network size, it can adapt to the computing power conditions of different hardware platforms and the real-time and low-power requirements of engineering deployment.