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An attention mechanism-based multi-domain feature fusion approach for active sonar target recognition

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Abstract: Due to the complex and changeable marine environment, the active sonar target recognition problem has always been difficult in the field of underwater acoustics. Deep learning-based fusion recognition technology provides an effective way to solve this problem, but relying on simple concatenation strategies to fuse multi-domain features can cause information redundancy, and it is not easy to effectively mine correlation information between domains. Therefore, this paper proposes an attention mechanism-based multi-domain feature fusion approach for active sonar target recognition. By preprocessing active sonar echo signals and constructing a multi-domain feature extraction and fusion network, this method uses a one-dimensional convolutional neural network with long short-term memory (1DCNN-LSTM) and a two-dimensional convolutional neural network (2DCNN) with channel attention introduced to extract deep features from different domains. Subsequently, combining feature concatenation and constructing multi-domain cross-attention, intra- and cross-domain feature fusion is performed, which can effectively eliminate redundant information and promote inter-domain information interaction, while maximizing the retention of target features. Experimental results show that compared with single-domain methods, the network using an attention mechanism for multi-domain feature fusion strengthens cross-domain information interaction and significantly improves feature representation capability. Compared with other methods, the proposed method has obvious advantages in performance and maintains stable generalization ability in scenarios with low signal-clutter ratios.

Key words: Acoustic target recognition; Neural network; Attention mechanism; Multi-domain feature fusion

1 Introduction

With the development of marine resource exploitation and national defense technology, the demand for underwater acoustic target recognition using sonar continues to grow (Li et al., 2024). Active sonar can achieve high-precision localization and recognition of targets in various underwater detection scenarios, holding significant importance in applications such as underwater search and rescue, fishing, seabed environment detection, and frogman/submarine detection (Huang and Li, 2019). However, the complex and variable marine environment poses numerous challenges for underwater acoustic target recognition (Domingos et al., 2022). First, during sound wave propagation, the multipath effect occurs due to reflections from the sea surface and seabed (Fang et al., 2019), while moving targets such as submarines, torpedoes, and underwater vehicles generate Doppler effects (Khan et al., 2024), leading to distortion of echo signals. Second, various types of clutter interference and noise exist in underwater environments, which may cover or confuse target signals, increasing recognition difficulty. Additionally, the high complexity and difficulty of underwater exploration result in a scarcity of samples, constraining the feature extraction capability of models and making it challenging to fully extract target feature information. Facing these problems, researchers have been continuously committed to research in this field.

Early underwater acoustic target recognition relied on manual listening to analyze the characteristics of acoustic signals (Arrabito et al., 2005), but this approach is susceptible to environmental and personnel factors, greatly limiting its recognition rate. With the development of computer science and the proposal and validation of signal processing techniques, the advancement of underwater target recognition technology has been promoted. Researchers have adopted machine learning methods to classify targets based on feature extraction. Shin et al. (1997) observed and analyzed the relationship between target echo signals and target shape/internal structure, extracting multiple features including time-domain waveforms,

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frequency spectra, time–frequency spectra, and auditory perceptual characteristics. By fusing the feature information and combining various machine learning algorithms such as neural networks, they achieved correct classification of target echoes and clutter. Young and Hines (2007) extracted multiple auditory perceptual features from target echo signals, performed feature screening using principal component analysis, and successfully distinguished echoes from offshore oil drilling platforms and cruise ships from various surrounding clutter by employing a Bayesian classifier model. However, traditional machine learning algorithms based on manual features—such as support vector machine (SVM) and *K*-nearest neighbor (KNN)—require expert experience or prior knowledge. Their capability to process large-scale, high-dimensional data is limited, making it difficult to fully mine deep-level information in the data and resulting in unsatisfactory target classification accuracy rates in complex underwater environments (Hu G et al., 2018).

With the rapid development of artificial intelligence technology, deep learning can automatically learn deep-level features from massive data (Liu et al., 2020), eliminating the need for cumbersome manual feature design. This provides an effective approach for underwater acoustic target recognition and has garnered widespread attention. Researchers have conducted studies mainly from two aspects: feature representation (Yang et al., 2016; Shadlou Jahromi et al., 2019; Han et al., 2022) and fusion strategies (Zhang et al., 2018; Hong et al., 2021; Hu G et al., 2021). At the feature extraction level, early researchers have focused on using neural networks for deep feature mining in a single domain. Lee et al. (2020) employed power-normalized cepstral coefficients to represent time-domain features, combined with a convolutional neural network (CNN) to accomplish target classification. Choo et al. (2024) performed short-time Fourier transform (STFT) time–frequency processing on a small number of real echo signals and achieved a high echo detection rate using a designed shallow neural network for target detection.

Given that echo signals are complex, time-varying, and exhibit strong inter-frame correlations, some researchers have attempted to use memory-capable neural networks such as recurrent neural network (RNN) and long short-term memory (LSTM) to process such signals. For example, Kamal et al. (2021) proposed a model combining one-dimensional convolutional neural network (1DCNN) and LSTM, specifically introducing a selective attention layer to focus on key features. In experiments on collected hydroacoustic data, this method achieved 95.2% recognition accuracy, demonstrating the advantage of incorporating attention mechanisms in feature extraction. However, the representational capability of single-domain features remains limited by signal dimensionality, making it difficult to distinguish targets in complex environments. Pan et al. (2025) constructed a multimodal deep learning model for ship-radiated noise recognition, feeding 1D time series and two-dimensional (2D) time–frequency images into a joint network to enhance recognition accuracy through cross-modal feature interaction. Wang et al. (2024) proposed an active target recognition method based on multi-domain active target echo images and attention networks, using a deep neural network with attention mechanisms to learn multi-domain joint feature representations, significantly improving target recognition accuracy compared to single-domain inputs.

Although many valuable achievements have been obtained, the combination of attention mechanisms and multi-domain fusion has shown potential in the field of underwater acoustic target recognition. Most existing methods adopt dual-domain interaction or single attention fusion approaches, failing to sufficiently explore the complex dependencies between cross-domain features, which leads to issues of feature redundancy and insufficient utilization of complementarity. Notably, attention mechanism-based multi-domain feature fusion has formed a mature application paradigm in fields such as computer vision and radar target recognition. He L et al. (2023) proposed the EnVLF framework for remote sensing cross-modal text–image retrieval, which integrates a vision Transformer module and a multi-modal encoder with cross-modal attention to align visual–text semantics and improve retrieval performance. Li et al. (2024) developed a multi-modal sentiment analysis model for image–text data; it uses DenseNet121 and convolutional block attention module (CBAM) to extract image emotional features and ALBert and BiLSTM to extract text features, and then adopts cross-attention for feature correlation modeling, enhancing classification accuracy. Gao et al. (2025) designed a method for multi-source remote sensing classification, extended Mamba to adapt to heterogeneous inputs (hyperspectral image and synthetic aperture radar (SAR) data), and enhanced cross-modal interaction via attention-like modeling, boosting fusion and classification effects. While these attention-based multi-domain/multi-modal fusion methods have achieved success in their fields, there remains ample room for exploration of such methods in active sonar target recognition. Building upon the aforementioned research, this paper proposes an attention mechanism-based multi-domain feature fusion approach for active sonar target recognition. By constructing a multi-domain cross-attention mechanism (MDCAM), it achieves cross-domain information interaction among time-domain envelope features, time–azimuth features, and time–frequency features, fully mining the multi-domain information of active sonar signals, thereby improving the accuracy of underwater acoustic target recognition and classification.

2 Overall framework of the method

The overall recognition flow of the attention mechanism-based multi-domain fusion recognition method for active sonar targets is shown in Fig. 1. This method consists of three modules: data preprocessing, multi-domain feature extraction and fusion, and classification and recognition. First, data preprocessing is performed on the active sonar echo signals to analyze different domains of the signals and provide inputs for subsequent feature extraction networks. Subsequently, through a multi-domain feature extraction and fusion network incorporating an attention mechanism, deep feature extraction and fusion of multi-domain features of the target are conducted to excavate inter-domain correlations and strengthen key information. Finally, the classification and recognition module performs classification and recognition on the fused multi-domain joint features.

In the data preprocessing module, the active sonar echo signals undergo time-domain, space–time-domain, and time–frequency-domain analysis, converting them into time-domain envelope sequences (ESs), space–time-domain time–azimuth images (TAIs), and time–frequency-domain time–frequency images, respectively.

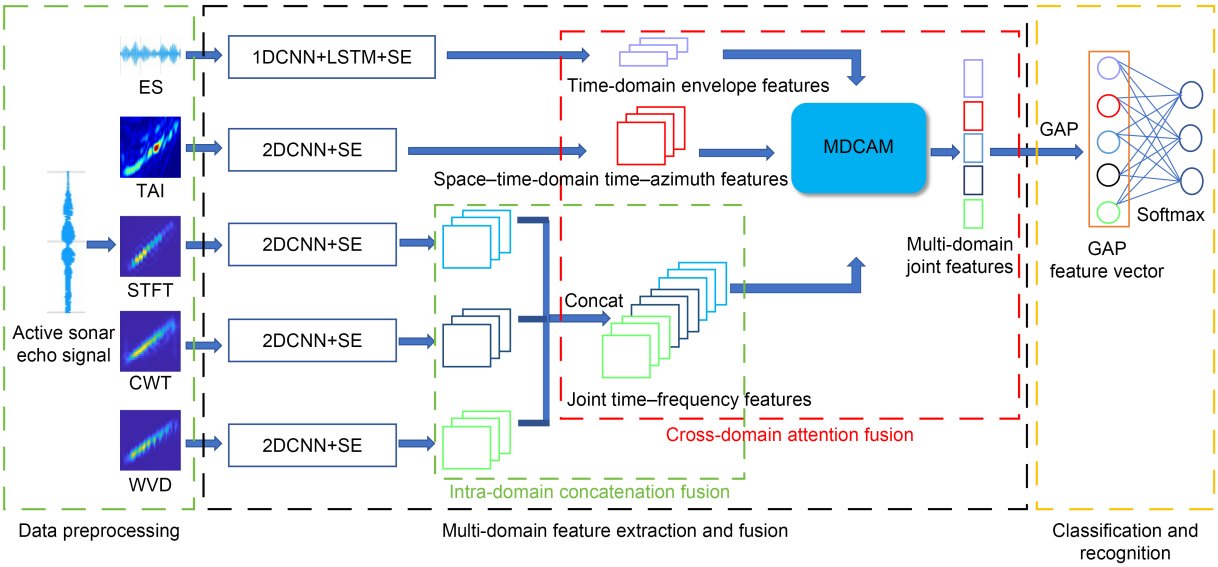

Fig. 1 Overall recognition workflow of the proposed method

For time-domain analysis, the modulus of the analytic signal is calculated via the Hilbert transform to extract the time-domain ES, reducing the influence of high-frequency carrier periodic oscillations while preserving low-frequency modulation information reflecting the slow-varying trends of target echo energy. In space–time-domain analysis, leveraging the advantage of prior knowledge about transmitted signals in active sonar echoes, matched filtering and space–time conversion are applied to generate 2D TAIs, which effectively characterizes the dynamic spatial–azimuth properties of targets. Because neither the time domain nor the frequency domain alone can capture the time-varying frequency characteristics of signals, and because the instantaneous frequency evolution of target echoes constitutes key discriminative information, three time–frequency transformation methods—STFT, continuous wavelet transform (CWT), and Wigner–Ville distribution (WVD)—are jointly employed for processing target echo signals in time–frequency-domain analysis.

In the multi-domain feature extraction and fusion module, first, 1DCNN-LSTM and 2DCNN are designed to extract features from different domains of signals, with the squeeze and excitation (SE) (Hu J et al., 2018) channel attention mechanism incorporated into each to perform adaptive weighting on the channel dimension of features from different domains. Its core idea is squeezing global feature statistical information and prompting the adaptive adjustment of channel weights, thereby strengthening key features and suppressing redundant information. Second, to overcome the limitations of traditional static fusion through simple concatenation and fully use complementary information from different domains of echo signals, feature concatenation is initially applied for intra-domain feature fusion, followed by the construction of an MDCAM. This mechanism performs cross-attention computation across multi-domain features, dynamically learning importance weights for features from different domains, thereby maximizing target feature retention while effectively eliminating redundant information and promoting inter-domain information interaction.

In the classification and recognition module, a lightweight classification architecture combining global average pooling (GAP) and Softmax is adopted for accurate and efficient classification of the fused multi-domain joint features. Unlike traditional fully connected (FC) layers, where excessive trainable parameters easily cause model overfitting, GAP aggregates feature maps through global mean pooling, mapping high-dimensional features to low-dimensional vectors without introducing additional trainable parameters and significantly enhancing model generalization capability. First, GAP operation is performed on the fused multi-domain joint features to generate feature vectors containing global information. Subsequently, these vectors are fed into the Softmax layer, where class probability distributions are computed via the normalized exponential function to achieve target classification. This design leverages the parameter-free nature and global information integration capability of GAP, reducing model complexity while preserving feature discriminability, effectively preventing overfitting and ensuring that underwater target classification results possess both high accuracy and good interpretability.

The multi-domain feature extraction and fusion module constitutes the key research focus of this paper and will be explained in detail below.

2.1 Multi-domain feature extraction based on channel attention

Aiming at the different representation forms of active sonar echo signals, differentiated deep network architectures are constructed to achieve hierarchical feature mining, and the channel attention mechanism is employed to enhance focus on important features. Specifically, a 1DCNN-LSTM serial network is adopted to extract time-domain envelope features of echo signals, while 2DCNN networks are used to extract space–time-domain time–azimuth features and time–frequency-domain time–frequency features. The SE channel attention mechanism is embedded into each network, adaptively adjusting channel weights through global pooling and nonlinear mapping to strengthen target-relevant features.

Among them, the SE mechanism effectively addresses the information redundancy problem caused by convolutional layers learning channel features through kernels. By adaptively assigning weights

to each channel of the feature map, it enables the network to focus on features more critical for target recognition, thereby enhancing channel-wise feature representation and suppressing interference from redundant information. As shown in Fig. 2, its structure is primarily composed of three parts: squeeze, excitation, and reweighting. Assume the input feature is $\boldsymbol{X}$, where H is the feature map height, W is the width, C is the number of channels, and r is the reduction ratio that controls the compression degree of feature channels in the excitation step. First, the compression operation of the SE module, namely, GAP applied to the input feature map, compresses spatial dimensions into channel descriptors. Subsequently, the excitation step uses two FC layers to perform a nonlinear transformation on the channel descriptors, learning dependencies between channels, with ReLU activation in the middle, and finally Sigmoid to generate weights. The reweighting step multiplies the channel weights with the original feature map channel by channel, enhancing key channel features and suppressing redundant channels, thus obtaining the weighted feature map.

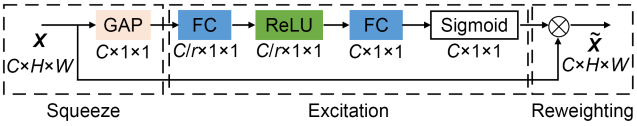

Fig. 2 Structure diagram of the SE channel attention mechanism

2.1.1 1DCNN-LSTM-SE time-domain feature extraction network

Traditional methods often use images transformed by time–frequency analysis as network model inputs, leading to loss of the time-domain information of the original signal. This paper takes the ES processed from active sonar echo signals through time-domain analysis as input. This ES focuses on the slow-varying trends of signal amplitude, effectively removing high-frequency carrier interference, and can completely preserve the time-domain dynamic information of target echoes. Aiming at the 1D time series characteristics of the ES, a 1DCNN-LSTM-SE time-domain feature extraction network is constructed, as shown in Fig. 3.

In the time-domain feature extraction network, the 1DCNN part consists of alternating convolutional layers and max-pooling layers. The convolutional layers contain 8, 16, and 32 convolution kernels with a size of 3, extracting local temporal features in the ES through sliding window operations. Its translation invariance effectively preserves the time-domain continuity of envelope features, avoiding feature extraction deviations caused by data shifts. The max-pooling layers use a pooling window of size 3 to reduce the dimensionality of the convolutional layers' outputs and lower computational complexity while preventing overfitting. Batch normalization (BN) layers and ReLU activation functions are added after the convolutional and pooling layers to prevent overfitting and improve model stability. This modular stacking design draws on the structural idea of ResNet, enabling multi-scale feature extraction through stacked modules, thus efficiently learning time-domain features under limited resources while keeping the network lightweight. Subsequently, the SE channel attention mechanism enhances the features output by the 1DCNN, dynamically strengthening target-relevant time-domain features through global pooling, channel weight learning, and feature reweighting. Finally, LSTM is used to further enhance the feature extraction capability for long-term temporal dependencies in the ES. It contains 64 memory units, selectively retaining or forgetting envelope feature information through gating mechanisms, thereby effectively capturing long-term dependencies in the ES. Its output feature vector serves as the complete time-domain envelope feature representation for subsequent feature fusion and target recognition tasks.

2.1.2 2DCNN-SE space–time–frequency-domain feature extraction network

For the 2D TAIs of the space–time domain and time–frequency images generated after the time–frequency domain, this paper constructs a 2DCNN network. To enhance the network's feature extraction capability for space–time–frequency-domain image features, 2DCNN is similarly combined with the SE channel attention mechanism.

By integrating the structural advantages of 2DCNN and SE, a 2DCNN-SE deep feature extraction network is ultimately constructed, as shown in Fig. 4. The 2DCNN part consists of alternating convolutional layers and max-pooling layers. The convolutional layers contain 8, 16, and 32 convolution kernels with a size of 3×3. The max-pooling layers use a 2×2 pooling window with a stride all set to 2, and BN layers and ReLU activation functions are added after the convolutional and pooling layers. Similarly, this hierarchical extraction of features at different scales via multiple modules can efficiently enhance feature representation capability and achieve lightweight deep feature learning. The SE part, while maintaining the

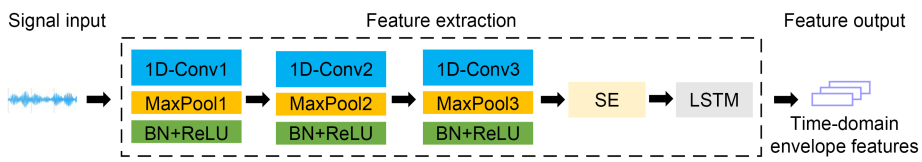

Fig. 3 Structure diagram of the 1DCNN-LSTM-SE time-domain feature extraction network

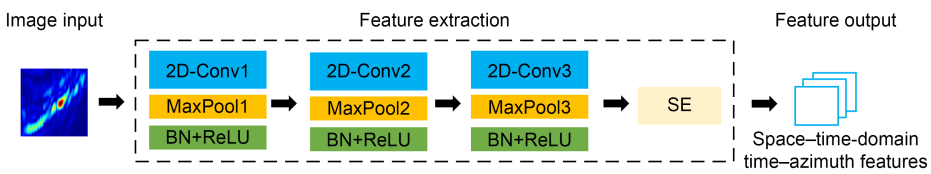

Fig. 4 Structure diagram of the 2DCNN-SE space–time–frequency-domain feature extraction network

deep feature extraction capability of 2DCNN, dynamically adjusts the weight of each channel through internal GAP and FC layers, enhancing key feature extraction capability and suppressing noise and redundant information.

2.2 Multi-domain feature fusion based on cross-attention

To fully use the time-domain envelope features of target echo signals, the time–azimuth features in the space–time domain, and the time–frequency features from different time–frequency analyses, we fuse both intra-domain and cross-domain features to achieve a more comprehensive representation and improve recognition performance. While multi-domain features provide diverse target characterizations, they may also introduce redundancy and increase computational complexity. Therefore, the key challenge in feature fusion is to maximize complementary information while reducing redundancy under limited hydroacoustic data conditions. In this study, we design intra-domain and cross-domain fusion strategies within the multi-domain feature fusion module. For intra-domain fusion, time–frequency features extracted from different time–frequency analyses are combined via feature concatenation to enhance single-domain representations and form a joint time–frequency feature. For cross-domain fusion, we employ an attention mechanism to adaptively weight and fuse features, learning inter-domain dependencies while suppressing redundancy and enabling complementary information integration. The resulting multi-domain joint feature provides richer discriminative information for target classification, significantly improving recognition performance in complex environments.

2.2.1 Intra-domain feature concatenation fusion

Prior to cross-domain fusion using multi-domain cross-attention, the time–frequency features extracted from STFT, CWT, and WVD time–frequency analyses via the 2DCNN-SE feature extraction network are fused through feature concatenation to form a joint time–frequency representation, maximizing the retention of time–frequency features of the target. Specifically, feature concatenation is performed along the channel dimension using a concatenation fusion layer, resulting in a unified time–frequency feature representation. Assuming that the feature maps extracted from the three time–frequency analysis methods are denoted as $\boldsymbol{F}_i \in \mathbb{R}^{C_i \times H \times W}$ (i=1, 2, 3), and the concatenated output feature is

$$\boldsymbol{F}_{\text{concat}} = \boldsymbol{F}_1 \oplus \boldsymbol{F}_2 \oplus \boldsymbol{F}_3 \in \mathbb{R}^{(C_1+C_2+C_3) \times H \times W}, \tag{1}$$

where $\oplus$ denotes the concatenation operation along the channel dimension, merging features from different time–frequency analysis methods. This process preserves the feature information from various time–frequency representations, providing a foundation for subsequent cross-domain fusion.

2.2.2 Cross-domain attention mechanism fusion

To address the challenges of distribution, scale, and type discrepancies across different domains, as well as the redundancy and computational complexity introduced by multi-feature fusion, traditional fusion methods often fail to fully exploit inter-domain dependencies, leading to insufficient information utilization. The attention mechanism, due to its ability to capture feature dependencies, offers an effective solution for multi-domain feature fusion. Therefore, this study proposes an MDCAM, which is an extension of the Transformer's multi-head attention mechanism (Vaswani et al., 2017). By combining self-attention and cross-domain attention, MDCAM enables deep interaction and adaptive fusion of time-domain, space–time-domain, and time–frequency features. The module consists of linear transformation layers, scaled dot-product attention, normalization layers, and feature concatenation layers, as illustrated in Fig. 5. Through MDCAM, the model learns nonlinear inter-domain dependencies, suppresses redundant information, enhances complementary features, and achieves efficient multi-domain feature fusion.

Specifically, the time-domain envelope features, space–time-domain time–azimuth features, and joint time–frequency features are input into their respective linear transformation layers to generate corresponding query ($\boldsymbol{Q}$), key ($\boldsymbol{K}$), and value ($\boldsymbol{V}$) matrices, as shown

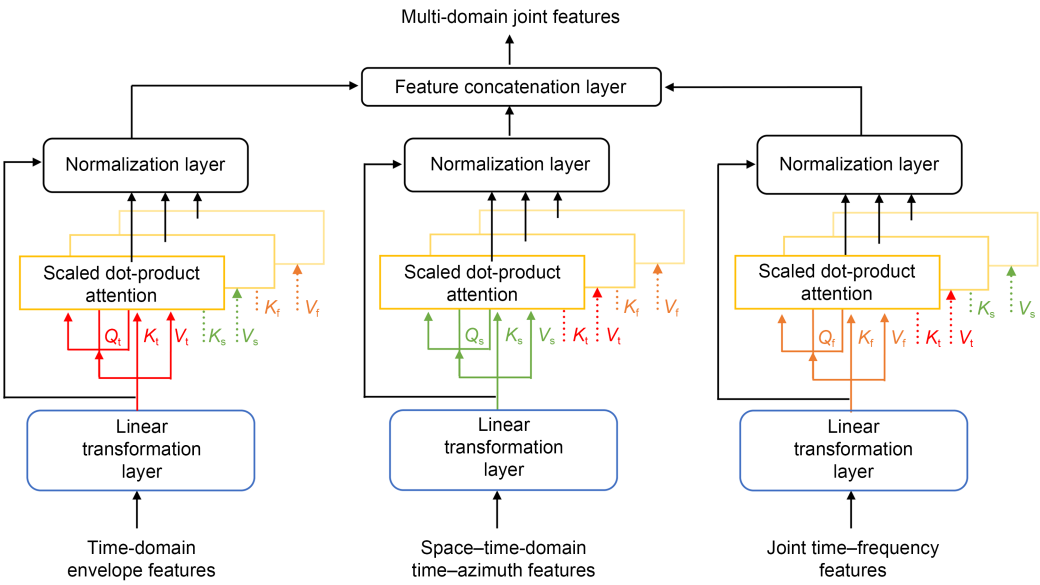

Fig. 5 Schematic diagram of feature fusion in the multi-domain cross-attention module

by the time-domain features ($\boldsymbol{Q}_t$, $\boldsymbol{K}_t$, $\boldsymbol{V}_t$), space–time-domain features ($\boldsymbol{Q}_s$, $\boldsymbol{K}_s$, $\boldsymbol{V}_s$), and time–frequency features ($\boldsymbol{Q}_f$, $\boldsymbol{K}_f$, $\boldsymbol{V}_f$) in Fig. 5. Subsequently, the computation proceeds to multi-head attention, which consists of two parts: self-attention computation and cross-domain attention computation. In self-attention computation, features within each domain undergo scaled dot-product attention calculation to capture intra-domain feature dependencies and enhance the expression of key information. In cross-domain attention computation, the $\boldsymbol{Q}$ from one domain interacts with the $\boldsymbol{K}$ and $\boldsymbol{V}$ from other domains to explore potential inter-domain correlations and achieve cross-domain information complementarity. Taking the time-domain envelope feature processing path as an example, and assuming the input time-domain feature $\boldsymbol{X}$ has dimension d, after passing through the linear transformation layer, the generated $\boldsymbol{Q}_t$ and the $\boldsymbol{K}_s$, $\boldsymbol{V}_s$ from the space–time-domain feature path are input into the scaled dot-product attention for cross-domain attention computation. The computation process can be expressed as

$$\text{Attention}(\boldsymbol{Q}_t, \boldsymbol{K}_s, \boldsymbol{V}_s) = \boldsymbol{V}_s \text{Softmax}\left(\frac{\boldsymbol{Q}_t \boldsymbol{K}_s^{\mathrm{T}}}{\sqrt{d_{K_s}}}\right). \tag{2}$$

Here, $\boldsymbol{Q}_t$, $\boldsymbol{K}_s$, and $\boldsymbol{V}_s$ are obtained through linear transformations using three different weight matrices $\boldsymbol{W}_q$, $\boldsymbol{W}_k$, and $\boldsymbol{W}_v$, respectively, e.g., $\boldsymbol{Q}_t = \boldsymbol{X}\boldsymbol{W}_q$. By multiplying $\boldsymbol{Q}_t$ with the $\boldsymbol{K}_s$ matrix, a correlation score matrix is obtained, which serves as a similarity measure between the time and space–time domains. This matrix is then normalized via Softmax to produce attention weights, which are used to weight $\boldsymbol{V}_s$, enabling the time-domain features to incorporate information from the space–time-domain features. After multi-head attention computation, the outputs of the multi-head attention are added to the input features and normalized. Finally, the features are integrated through a concatenation layer to produce the joint multi-domain feature output.

The cross-domain feature fusion approach based on multi-domain cross-attention not only enhances inter-domain interaction, allowing features from different domains to guide and complement each other, but also enables the model to adaptively filter irrelevant information and focus on complementary features through the synergistic effect of self-attention and cross-domain attention. Moreover, compared to traditional multi-branch attention structures, MDCAM significantly reduces the number of parameters by sharing the multi-head attention module while maintaining performance and improving computational efficiency.

3 Method validation

3.1 Experimental description and data analysis

The active sonar echo signal experiment was conducted at the Mogan Lake underwater acoustic test site. The transmitted signal employed a linear frequency modulated (LFM) waveform with a pulse width of 2 ms and a frequency range of 40–80 kHz, sampled at 1 MHz. Fig. 6 illustrates the experimental target placement configuration. The transducer, hydrophone, and target were positioned at the same depth, with the hydrophone placed between the transducer and the target rotation platform. The target was slowly rotated via the platform.

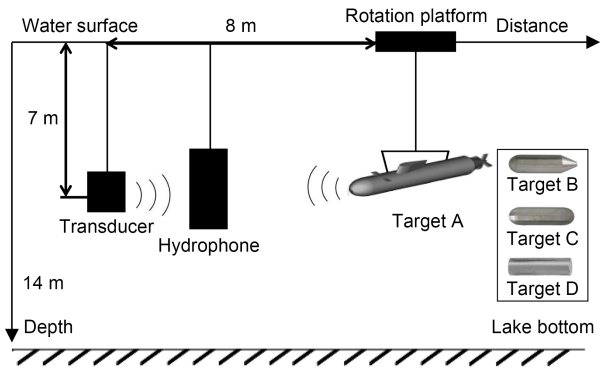

Fig. 6 Schematic diagram of target placement

The sonar signals were emitted by the transducer, propagated toward the target, and received by the hydrophone after reflection.

The experiment used four types of submarine-like cylindrical models as targets: submarine model (target A), cylinder with hemispherical head and conical tail (target B), cylinder with both hemispherical head and tail (target C), and standard cylindrical model (target D). All four targets had similar materials and shapes, making their features difficult to distinguish in the interference-rich lake test data. The signal waveforms are shown in Fig. 7, each with 2400 sampling points. A total of 600–900 signal samples were collected for each target category. After data preprocessing, time-domain ESs, space–time-domain TAIs, and time–frequency images were generated, labeled with category tags to form the sample dataset, which was then divided into training and test sets in a 7:3 ratio.

3.2 Data preprocessing

The active sonar echo signals were analyzed in different domains and converted into time-domain ESs, space–time-domain TAIs, and time–frequency images. In Fig. 8a, the time-domain ES had a horizontal axis representing the time domain (containing 2400 sampling points) and a vertical axis representing the envelope amplitude, reflecting low-frequency modulation information of the target echo energy's gradual variation trend. In Fig. 8b, the space–time-domain TAI had a horizontal axis representing 200 detection beams covering a 90° azimuth angle and a vertical axis representing the signal time series (covering a 2.2 ms time range), effectively characterizing the dynamic spatial azimuth characteristics of rotating targets. In Figs. 8c–8e, note the following for the time–frequency images: In the STFT time–frequency image, the horizontal axis represents segmented time frames and the vertical axis represents normalized frequency. In the CWT and WVD time–frequency images, the horizontal axis represents time sampling points and the vertical axis represents the actual frequency, presenting the frequency variation patterns over time through different time–frequency transforms.

3.3 Experimental results and analysis

All experiments were conducted on an NVIDIA GeForce RTX 3080 server. Models were trained for 100 epochs with full convergence achieved. The batch size was set to 32, and the initial learning rate was 10^{-5}, halved at the 50th and 75th epochs to facilitate model fine-tuning and prevent overfitting. Optimization used the Adam optimizer. Evaluation metrics included accuracy (Acc), F1-score

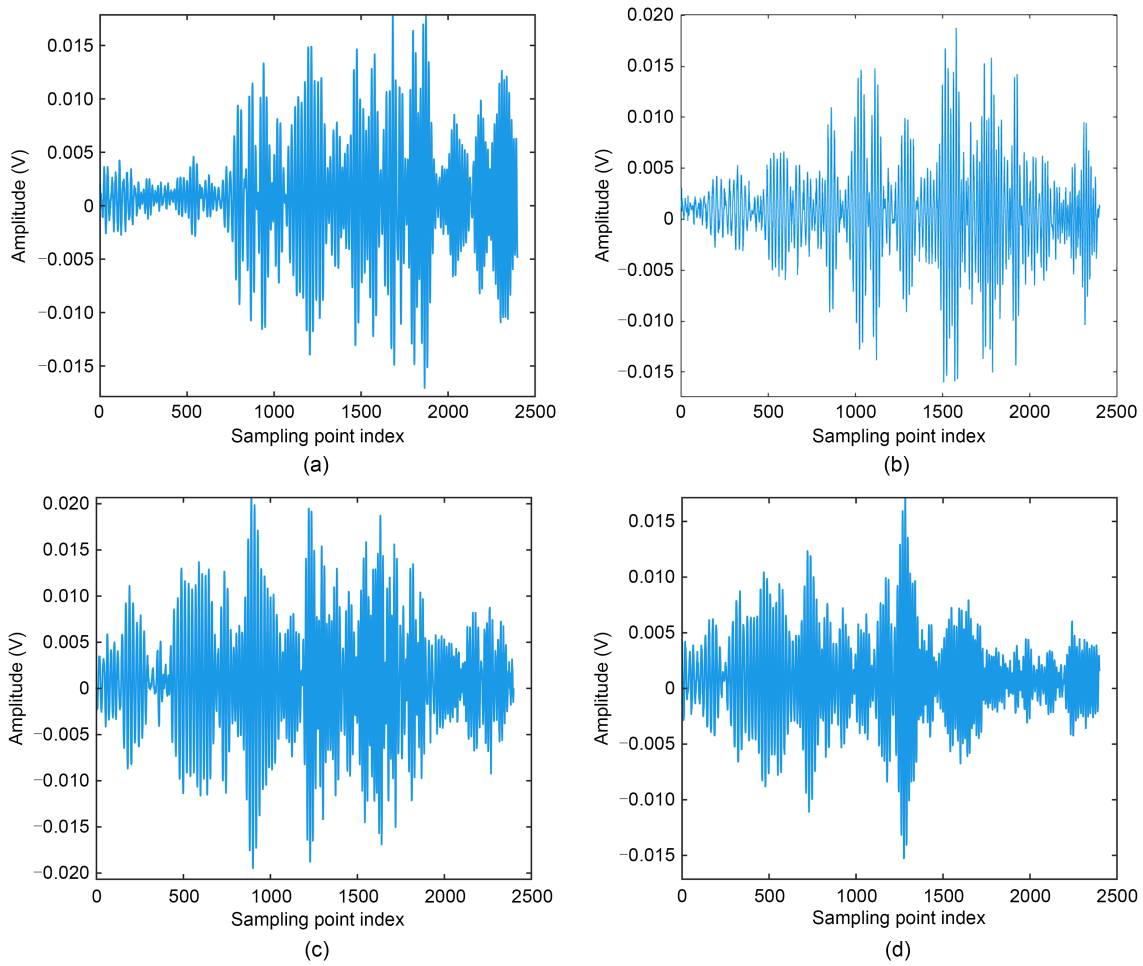

Fig. 7 Comparison of echo signals from four target types: (a) target A; (b) target B; (c) target C; (d) target D

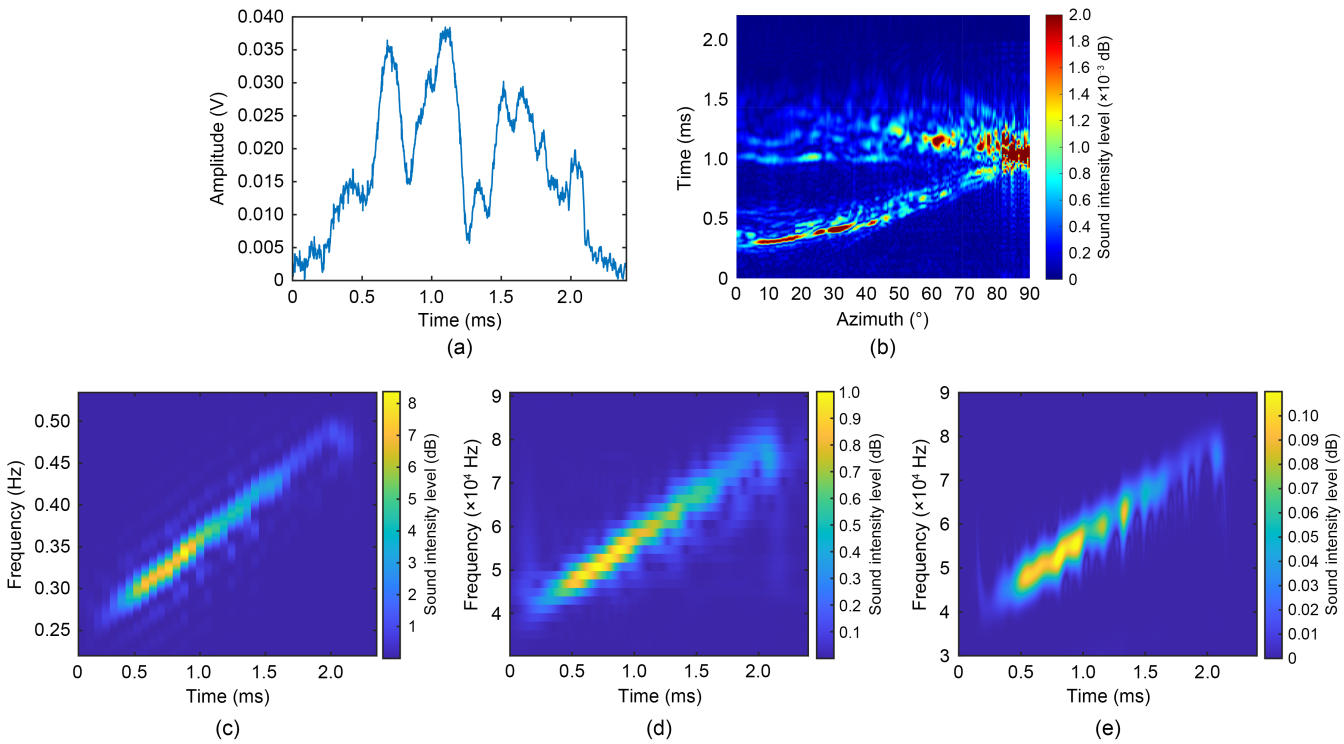

Fig. 8 Preprocessing results of target echo signal data: (a) time-domain ES; (b) TAI; (c) STFT time–frequency image; (d) CWT time–frequency image; (e) WVD time–frequency image

(F1), and recall (R), supplemented by feature visualizations to comprehensively assess network performance on the test set. To validate the effectiveness of the proposed attention-based multi-domain feature fusion method for active sonar target recognition, ablation studies were performed on the attention mechanisms in multi-domain feature extraction and multi-modal feature fusion modules, along with comparative experiments against other network models.

3.3.1 Performance validation of integrated channel attention

To verify the effectiveness of incorporating the SE channel attention mechanism in multi-domain feature extraction, we first compared the performance between each basic network and the network integrated with the SE channel attention mechanism. We further introduced mainstream attention mechanisms, such as CBAM and efficient channel attention (ECA), for horizontal comparison with SE to clarify the adaptability of different attention mechanisms for the task in this study. The experimental results are shown in Tables 1 and 2.

From the perspective of channel attention integration in Table 1, when using time-domain ES as input to the LSTM network, its classification accuracy and F1-score slightly outperform the counterparts of 1DCNN, demonstrating LSTM's advantage in capturing long-term temporal dependencies. The series combination of 1DCNN and LSTM further improves performance, indicating complementary integration of local features and global temporal characteristics. After introducing the SE module, the model shows significant enhancement, strengthening the representation capability for time-domain envelope features. For space–time-domain TAI and time–frequency images, the 2DCNN-SE model with SE attention substantially outperforms conventional 2DCNN, confirming that the SE mechanism adaptively weights channel features to suppress redundant information and focus on critical patterns, validating the effectiveness of attention mechanisms in enhancing discriminative power for 2D feature extraction.

Additionally, the optimal performance metrics across domains are shown in Table 1. The CWT time–frequency image achieves the highest accuracy (90.07%) in the time–frequency domain, highlighting its superiority in capturing fine-grained target features. This stems from the CWT's flexible dilation and translation parameters, which adapt to complex time–frequency variations in echoes and extract subtle signal characteristics. In contrast, STFT offers high computational efficiency but limited frequency resolution. WVD provides high time–frequency resolution but suffers from cross-term interference. Both STFT and WVD underperform CWT in comprehensive feature extraction. Time-domain ESs contain discriminative information but yield lower accuracy and F1-scores than other domains, indicating weaker separability and necessitating multi-domain fusion for precise recognition.

Based on the horizontal comparison results of different attention mechanisms in Table 2, CBAM slightly outperforms the SE mechanism in some models. For instance, the classification accuracy reaches 86.72% when using STFT time–frequency images as input. However, as a hybrid attention mechanism that considers both channel attention and spatial attention, CBAM increases the model parameter count by approximately 17% compared to SE. This significant rise in computational complexity hinders its application in

Table 1 Experimental results of multi-domain feature extraction

Domain	Input data	Network model	Acc (%)	F1 (%)
Time domain	ES	1DCNN	82.82	73.14
		LSTM	83.35	73.43
		1DCNN-LSTM	84.05	74.01
		1DCNN-LSTM-SE	85.71	75.38
Space–time domain	TAI	2DCNN	84.56	73.89
		2DCNN-SE	86.42	75.93
Time–frequency domain	STFT time–frequency image	2DCNN	84.90	74.37
		2DCNN-SE	86.70	76.20
	CWT time–frequency image	2DCNN	88.43	78.15
		2DCNN-SE	90.07	79.41
	WVD time–frequency image	2DCNN	86.71	76.83
		2DCNN-SE	88.49	78.56

Table 2 Experimental results of different attention mechanisms

Domain	Input data	Network model	Acc (%)	F1 (%)	Parameter count ($\times 10^6$)
Time domain	ES	1DCNN-LSTM-CBAM	85.83	75.42	9.2
		1DCNN-LSTM-ECA	85.12	74.96	7.8
		1DCNN-LSTM-SE	85.71	75.38	8.1
Space–time domain	TAI	2DCNN-CBAM	86.57	76.01	7.4
		2DCNN-ECA	85.85	75.48	6.1
		2DCNN-SE	86.42	75.93	6.3
Time–frequency domain	STFT time–frequency image	2DCNN-CBAM	86.72	76.25	7.5
		2DCNN-ECA	86.03	75.62	6.2
		2DCNN-SE	86.70	76.20	6.4

real-time sonar systems. Although the ECA mechanism reduces the model parameter count by about 3% compared to SE through simplifying the channel attention computation, it ignores the nonlinear dependencies between channels. Consequently, it insufficiently captures the complex cross-channel correlations of sonar signals, leading to generally lower performance than SE. In contrast, the SE channel attention mechanism achieves a balance among classification accuracy, model performance, and lightweight design, making it more suitable for the active sonar target recognition scenario.

3.3.2 Performance validation of integrated cross-attention

To comprehensively evaluate the effectiveness of multi-domain feature fusion and the advantages of the proposed MDCAM in fusion, we have conducted experiments in two parts. The first part is aimed to analyze the complementarity of features from different domains by comparing single-domain, intra-domain, and cross-domain combinations, as well as multi-domain feature fusion. The second part is aimed to verify the unique advantages of MDCAM in cross-domain information interaction and redundancy suppression by introducing other mainstream feature fusion strategies for comparison.

The experimental results of multi-domain feature fusion comparison are shown in Table 3. Taking the single-domain CWT time–frequency image as an example, the 2DCNN-SE model achieves 90.07% accuracy. After feature fusion, performance is improved substantially: fusion of CWT and ES via Concat increases accuracy to 90.60%, while MDCAM attention fusion reaches 92.07%. Similarly, the maximum accuracy of combining CWT time–frequency images with space–time-domain TAIs rises to 93.49%. For multi-domain fusion, the accuracy of integrating time–frequency images, TAIs, and ESs through hybrid Concat and MDCAM reaches as high as 95.13%.

To intuitively demonstrate the performance differences among different domain combinations, the accuracy of various domains is further compared, as shown in Fig. 9. Compared with single-domain approaches, multi-domain feature fusion achieves significantly superior recognition performance, indicating that synergistic effects are realized by integrating feature information from different domains. Notably, the CWT time–frequency image achieves the highest accuracy among all single-domain inputs. However, intra-domain fusion of CWT and WVD time–frequency images does not yield a significant accuracy improvement, reflecting that intra-domain features may contain substantial redundant information with relatively limited complementarity, making it difficult to achieve a substantial boost in recognition performance. On the other hand, cross-domain fusion of CWT time–frequency images with either ESs or TAIs increases the accuracy by more than 2%, demonstrating the potential of cross-domain information complementarity to enhance feature representation. Additionally, after integrating all time–frequency images from the time–frequency domain with other domains for cross-domain fusion, although the computational burden caused by the additional spectra is slightly increased, the improved accuracy validates the necessity of their integration. It can be inferred from the above experimental analysis that, whether additional features from other domains or the same domain can improve recognition performance, depends on their ability to provide complementary or unique information. Therefore, achieving synergistic effects through integrating

Table 3 Experimental results of multi-domain feature fusion

Domain	Input data	Feature extraction	Feature fusion	Acc (%)
Single domain	CWT time–frequency image	2DCNN-SE		90.07
Combined domains	CWT time–frequency image and ES	1DCNN-LSTM-SE and 2DCNN-SE	Concat	90.60
	CWT time–frequency image and ES	1DCNN-LSTM-SE and 2DCNN-SE	MDCAM	92.07
	CWT time–frequency image and TAI	2DCNN-SE	Concat	91.65
	CWT time–frequency image and TAI	2DCNN-SE	MDCAM	93.49
Multi-domain	CWT image, TAI, and ES	1DCNN-LSTM-SE and 2DCNN-SE	Concat	92.52
	CWT image, TAI, and ES	1DCNN-LSTM-SE and 2DCNN-SE	MDCAM	94.76
	Time–frequency images*, TAI, and ES	1DCNN-LSTM-SE and 2DCNN-SE	Concat and MDCAM	95.13

* Referring collectively to the time–frequency images generated by STFT, CWT, and WVD

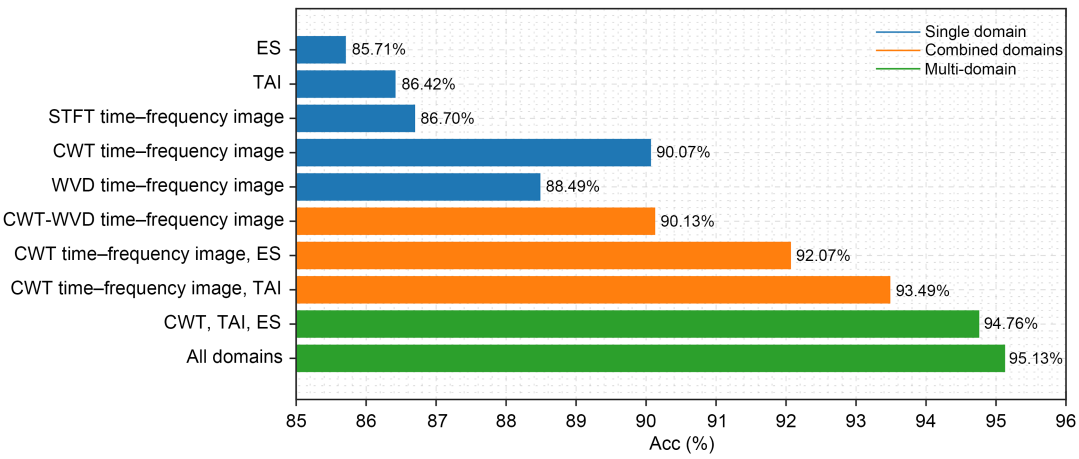

Fig. 9 Comparison of accuracy among single-, combined-, and multi-domain approaches

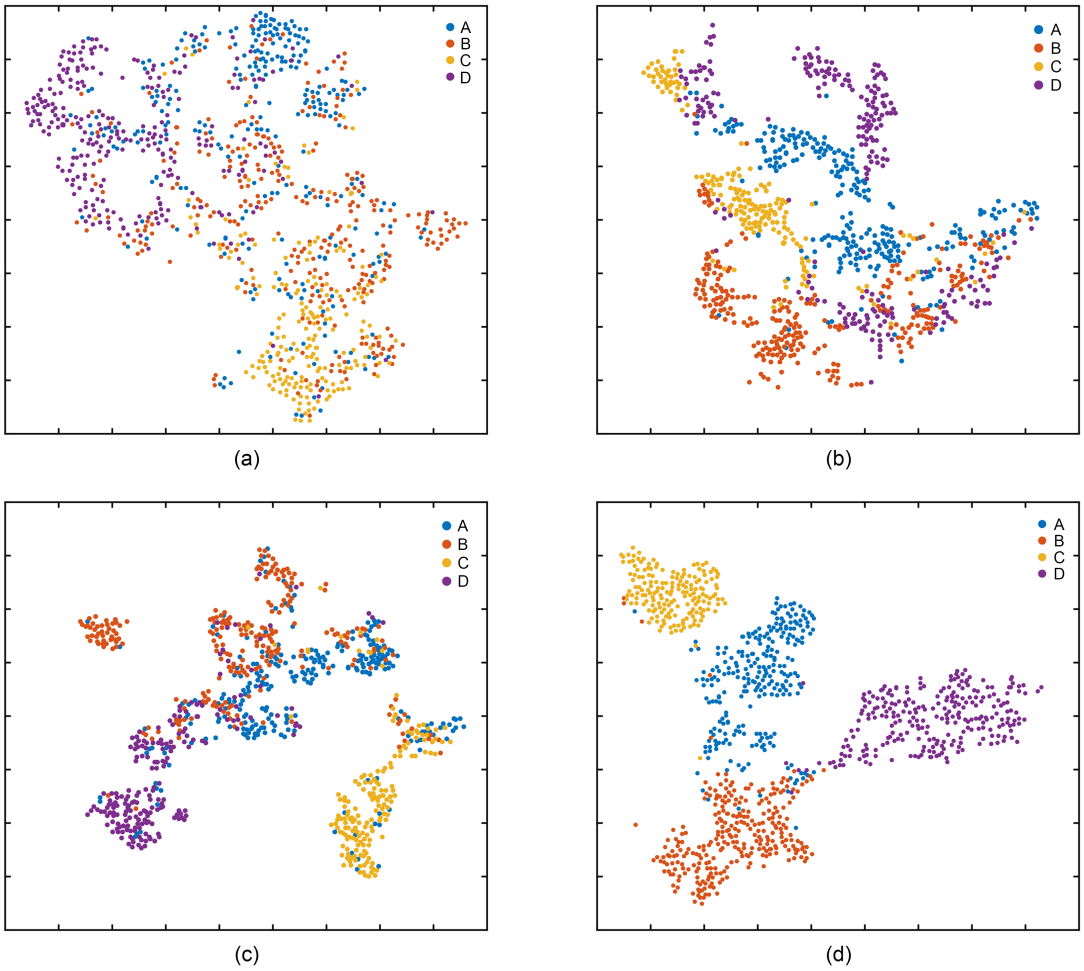

Fig. 10 Visualization comparison of output features using different methods: (a) raw data; (b) CWT time–frequency image; (c) CWT time–frequency image and ES; (d) multi-domain feature fusion

information from different domains facilitates the model in learning more comprehensive and abundant target information, thereby significantly enhancing recognition performance and verifying the significant advantages of multi-domain feature fusion in target recognition.

To visually validate the classification capability, *t*-distributed stochastic neighbor embedding (*t*-SNE) visualizes test set features in Fig. 10. In Fig. 10a, raw data show severe mixing of all four target classes. Using only CWT time–frequency image in Fig. 10b, classes A and B points exhibit extensive overlap, indicating confusion at class boundaries. Introducing cross-domain features (e.g., ESs) improves inter-class separation but retains local overlaps. In contrast, the proposed MDCAM fusion method in Fig. 10d forms compact clusters with distinct inter-class margins, nearly eliminating the overlap between classes A and B. This visually confirms that MDCAM effectively extracts complementary cross-domain features, significantly enhancing discriminative power and demonstrating classification superiority.

To further verify the unique advantages of MDCAM in cross-domain information interaction and redundancy suppression, other mainstream feature fusion strategies are introduced for comparison in this subsection. The experiments uniformly adopt CWT time–frequency images, ESs, and TAIs as multi-domain inputs, and the comparative experimental results of different feature fusion strategies are shown in Table 4.

Table 4 Comparative experimental results of different feature fusion strategies

Feature fusion	Acc (%)	F1 (%)	Parameter count ($\times 10^6$)	FLOP ($\times 10^9$)
Concat	92.52	90.35	38.81	1.76
Transformer	93.87	91.72	95.47	3.89
AdaFusion	94.12	91.68	62.76	2.93
MDCAM	94.76	92.12	58.12	2.37

FLOP: floating point operation

From the comparative results in Table 4, it can be observed that the traditional Concat fusion method, despite having a slightly lower parameter count, merely stacks features without exploring inter-domain dependencies, resulting in the weakest feature discriminability. Benefiting from the global modeling capability of the self-attention mechanism, the Transformer fusion strategy achieves a significant accuracy of 93.87%. However, this method requires global attention computation for all features, leading to a high parameter count that makes it difficult to adapt to real-time sonar recognition scenarios. Meanwhile, AdaFusion assigns feature weights through adaptive weighting, outperforming the Transformer fusion. Nevertheless, its weight assignment is only based on statistical information of a single feature dimension, failing to achieve dynamic interaction of cross-domain features, thus still having limitations in complex sonar

signal processing. The proposed MDCAM achieves the optimal performance. This is attributed to its cross-attention computation tailored to the multi-domain characteristics of sonar signals: it can not only adaptively learn the importance weights of features from different domains, strengthen cross-domain information interaction, effectively suppress redundancy, and explore inter-domain complementary features, but also avoid the redundant computation of the Transformer's global attention, thereby achieving an optimal balance between performance and efficiency.

3.3.3 Comparative experiments

To validate the effectiveness of the proposed MDCAM for active sonar target recognition, this subsection compares the proposed method with other models on the test set using recognition accuracy, recall, F1-score, and parameter count as evaluation metrics. Comparative models include the classical CNN VGG16 (Simonyan and Zisserman, 2015), the self-attention-based network model Vision Transformer (ViT) (Dosovitskiy et al., 2021), a method using 1DCNN-LSTM to extract deep temporal features of signals (Han et al., 2022), a method combining 1DCNN-LSTM with 2DCNN and employing SE channel attention for multi-feature fusion (Pan et al., 2025), and the method by Wang et al. (2024) that learns multi-domain joint features based on ResNet50 (He KM et al., 2016) and the swim Transformer attention mechanism.

The comparative experimental results are shown in Table 5. The proposed method significantly outperforms others in classification accuracy, recall, and F1-score. Compared with VGG16, the accuracy of the proposed method increases by 7.83 percentage points (PPs), recall increases by 4.05 PPs, F1-score increases by 4.44 PPs, while the model parameter count decreases by 48.87×10^6. Versus ViT, its accuracy increases by 6.55 PPs, recall increases by 4.79 PPs, and F1-score increases by 4.16 PPs, achieving superior recognition accuracy with a comparable parameter count. Compared with Han et al. (2022)'s time-domain-only method, the proposed multi-domain fusion (incorporating time-domain envelope features, space–time-domain time–azimuth features, and joint time–frequency features) enhances accuracy by 4.64 despite a higher parameter count. Relative to Pan et al. (2025)'s SE channel attention method and Wang et al. (2024)'s Transformer attention method, accuracy increases by 2.06 PPs and 1.28 PPs, recall increases by 1.34 PPs and 1.38 PPs, and F1-score increases by 1.80 PPs and 1.21 PPs, respectively. These advantages originate from MDCAM, which adaptively weights cross-domain features, enhances inter-domain interactions, suppresses redundancy, and exploits complementary patterns while maintaining parameter efficiency, validating the superiority and effectiveness of the proposed model.

Table 5 Comparative experimental results of our model and other models

Model	Acc (%)	R (%)	F1 (%)	Parameter count (×10^6)	FLOP (×10^9)
VGG16	87.30	88.16	87.81	134.27	3.72
ViT	88.58	87.42	88.09	85.67	3.42
Han et al.'s	90.49	88.45	88.23	44.66	2.13
Pan et al.'s	93.07	90.87	90.45	129.02	3.65
Wang et al.'s	93.85	90.83	91.04	138.56	3.93
Ours	95.13	92.21	92.25	85.40	2.84

Additionally, comparative validation has been performed on echo signals under different signal-to-reverberation ratios (SRRs). The accuracy comparison of various models is shown in Fig. 11. The proposed method maintains accuracy above 94% at 0–10 dB SRR, while Han et al.'s model shows significant degradation. Pan et al.'s and Wang et al.'s models sustain accuracy above 92%, with the proposed method outperforming them by approximately 2%. Under lower SRR conditions (−10 dB–0), the proposed model still achieves over 90% accuracy, surpassing all other comparative models. These results fully demonstrate that the proposed method, leveraging MDCAM, effectively captures complex dependencies among multi-domain features, generates more discriminative joint representations, significantly enhances underwater target recognition accuracy, and exhibits stronger robustness in low-SRR environments.

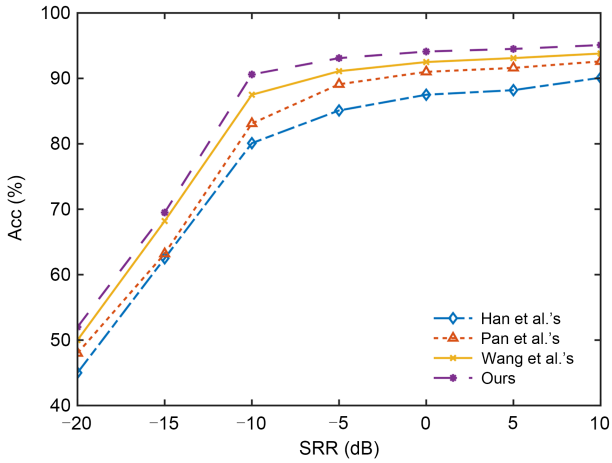

Fig. 11 Comparison of model accuracy under different SRRs

4 Conclusions

To fully exploit the multi-domain information of active sonar signals and improve the accuracy of underwater target recognition and classification, this paper proposes an attention mechanism-based multi-domain feature fusion approach for active sonar target recognition. The method achieves cross-domain information interaction of time-domain envelope features, time–azimuth features, and time–frequency features by constructing an MDCAM. The method preprocesses active sonar echo signals and establishes a multi-domain feature extraction network, which includes a 1DCNN-LSTM series network and a 2DCNN network, both incorporating channel attention mechanisms to extract deep features from different domains. By combining feature concatenation and attention mechanisms for intra-domain and cross-domain feature fusion, the target classification accuracy is improved. The experimental results show that compared with single-domain methods, the network using an attention mechanism for multi-domain feature fusion enhances cross-domain information interaction, significantly improves feature representation capability, achieves notably higher recognition accuracy than other methods, and maintains stable generalization capability in low-SRR scenarios.

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Author contributions

Tongjing SUN conducted formal analysis, carried out investigation, acquired resources, reviewed and edited the paper, acquired funding, and provided supervision. Haoran XU designed the research concept, processed the data, carried out investigation, developed the methodology, and drafted the paper. Shishuo REN carried out investigation, assisted in methodology development, and conducted validation. Denghui ZHANG processed the data, conducted formal analysis, and reviewed and edited the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used ChatGPT to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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