Multi-strategy Optimization for Cross-modal Pedestrian Re-identification Based on Deep Q-Network Reinforcement Learning

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Cross-modal pedestrian re-identification (C-ReID) is a crucial task in computer vision, aiming to match pedestrian identities across different modalities of data. This paper proposes a reinforcement learning-based framework, RLCMPRF, to tackle the challenges of modality variability, data diversity, annotation difficulties, and optimal strategy selection. RLCMPRF uses deep Q-network (DQN) reinforcement learning to dynamically select the best feature extraction and matching strategies, ensuring robustness against these challenges. We introduce a dual-stream network to process multimodal images, followed by a feature fusion layer for integration. The DQN-based strategy learning is complemented by a reward function designed to optimize matching accuracy, speed, and robustness. Experimental results demonstrate that RLCMPRF outperforms state-of-the-art methods based on deep learning, attention mechanisms, meta-learning, and generative adversarial networks. RLCMPRF achieves a success rate of 82% and an average cumulative reward of 150, showing improvements in convergence speed and generalization ability across multiple datasets.

Povzetek: Opisan je okvir za ponovno identifikacijo prehodov med modalnostmi, ki temelji na ojačitvenem učenju z več strategijami in uporablja globoko Q-mrežo (DQN). RLCMPRF uporablja dvotokovno mrežo in DQN za dinamično izbiro strategij ekstrakcije in ujemanja značilnosti.

1 Introduction

With the acceleration of urbanization and the growth of social security needs, video surveillance systems play an increasingly important role in maintaining public safety [1]. Pedestrian Re-Identification (ReID), as a key research direction in the field of video surveillance, aims to recognize images or video clips of the same pedestrian from different camera views. This technique has a wide range of applications in various fields such as crowd management, crime prevention, and traffic monitoring [2].

Traditional pedestrian re-recognition mainly focuses on the unimodal (usually RGB visible light images) case, in which the system needs to process data from the same sensor type. However, in real-world application scenarios, single-modal data is often difficult to meet the requirements of high-precision recognition due to factors such as changes in ambient lighting conditions, the influence of occlusions, and differences in camera viewpoints [3]. Therefore, cross-modal pedestrian re-recognition emerges, which involves the matching problem between different modal data, such as the matching between visible light images and infrared images. By introducing cross-modal information, the above limitations can be overcome to a certain extent, thus improving the accuracy and robustness of recognition [4].

Cross-modal pedestrian re-recognition is not only limited to matching between visible and non-visible images, but can also be extended to other forms of data fusion, such as matching between RGB images and depth maps, contour maps, and so on. In different application scenarios, such as nighttime surveillance, bad weather conditions or special environments, cross-modal pedestrian re-recognition can better cope with various complex situations, which provides the possibility of realizing all-weather and all-time effective surveillance [5]. However, cross-modal pedestrian re-recognition faces many challenges. The first is the inter-modal variability problem, the information collected by different types of sensors is inherently different, how to effectively extract and match this information is the key to the research. Second is the diversity of data, including the diversity of viewpoints, poses, and occlusions, which increases the difficulty of feature extraction and matching. In addition, the heavy workload and high cost of data labeling is also a major challenge for current research [6].

To address the above challenges, this study aims to explore a new solution - the use of Reinforcement Learning (RL) techniques for cross-modal pedestrian re-identification. Reinforcement learning, as a machine learning method that enables an intelligent body to learn optimal behavioral strategies by interacting with its environment, excels in handling complex decision-making problems. We believe that by applying reinforcement learning to cross-modal pedestrian re-identification, the problems of inter-modal variability, data diversity, and labeling difficulties can be effectively addressed to improve the overall performance of the system.

The novelty of the RLCMPRF framework lies in its integration of reinforcement learning, multi-task learning and probabilistic graph models, which innovatively solves the limitations of existing SOTA algorithms. Its necessity lies in its ability to effectively deal with problems such as noise sensitivity, inefficient big data processing, inaccurate category recognition and poor robustness, providing a breakthrough solution for research in the field.

2 Related work

2.1 Existing pedestrian re-identification methods

Pedestrian Re-Identification (ReID) is the process of detecting and recognizing the same individual under different camera viewpoints. In recent years, with the development of computer vision technology and deep learning, pedestrian re-recognition has become an active research field. Most of the early pedestrian re-recognition methods rely on hand-designed feature descriptors, such as SIFT (Scale-Invariant Feature Transform), HOG (Histogram of Oriented Gradients), etc [7, 8]. However, these methods are not effective when facing occlusion, illumination changes and perspective changes in complex environments. With the rise of deep learning techniques, Convolutional Neural Networks (CNNs) have been widely used in pedestrian re-recognition tasks due to their powerful feature extraction capabilities [9]. A method called Joint ReID and Attribute Recognition Network (JAN) has been proposed in the literature, which significantly improves the accuracy of the recognition by jointly training the pedestrian reidentification and attribute recognition tasks. Another work proposed in the literature introduces an attention mechanism that allows the model to focus on key regions in the pedestrian image, thus improving the robustness of the recognition.

Recent research has addressed various challenges in network performance and computer vision. Chydzinski and Adamczyk studied the burst ratio of packet losses in individual network flows, shedding light on network reliability and data loss patterns in communication systems [10]. On the other hand, Bassel et al. introduced PFA-GAN, a pose face augmentation method based on generative adversarial networks, contributing to advancements in face recognition and augmentation technology for improved model training in computer vision applications [11].

In addition to CNN-based approaches, some researchers have begun to explore the application of recurrent neural networks (RNNs) in pedestrian re-recognition. The literature proposes a model based on Long Short-Term Memory Networks (LSTMs) for capturing the dynamics of pedestrians between frames, which is particularly effective for handling the task of pedestrian re-recognition in video sequences [12].

2.2 Challenges in cross-modal pedestrian re-identification

Although deep learning techniques have achieved significant results in unimodal pedestrian re-recognition, unimodal methods still have limitations in practical applications due to the diversity of environmental factors, such as light changes and view angle changes. Cross-modal pedestrian re-recognition aims to overcome these problems by integrating multiple different types of data sources, such as matching between RGB images and infrared images, RGB images and depth maps. Lighting variations are a major challenge for cross-modal pedestrian re-identification. The appearance of a pedestrian image can vary significantly between daytime and nighttime, or between indoor and outdoor environments. To cope with the effects of illumination variations, some researchers have proposed methods based on multimodal feature fusion. For example, a framework called Cross-Modality Person Re-ID Network (CM-ReIDNet) has been proposed in the literature, which realizes feature alignment between RGB images and infrared images by sharing encoders and decoders, thus improving the performance of cross-modal recognition [13]. Perspective change is also another common problem. When pedestrians are in different positions or postures, their appearance features change significantly. A method called Pose-Guided Person Re-identification Network (PReNet) has been proposed in the literature, which enhances the robustness of the model to changes in viewing angle by estimating the pedestrian's pose and using it as an additional input [14].

2.3 Application of reinforcement learning to pedestrian re-identification

In recent years, reinforcement learning has begun to emerge in the field of pedestrian re-recognition as an effective decision-making tool. Unlike traditional supervised learning, reinforcement learning allows intelligences to learn optimal strategies through interaction with the environment, which provides new ideas for solving dynamic decision-making problems in pedestrian re-recognition. The literature proposes a reinforcement learning-based framework for pedestrian re-identification, which utilizes reinforcement learning to dynamically select the most effective feature extraction module and matching strategy. Experimental results show that this approach performs well in handling cross-domain pedestrian re-recognition tasks, especially when faced with the problem of domain transfer between different data sources [15]. The literature has designed a multi-stage reinforcement learning framework which first determines the optimal feature representation through reinforcement learning, and then uses a reinforcement learning strategy to guide the feature matching process in the second stage. This approach not only improves the accuracy of recognition, but also demonstrates good generalization ability [16].

Table 1: Research status

Algorithm Name	Accuracy	Recall	F1 Score	Run Time	Memory Consumption
Algorithm A	95.2%	93.5%	94.3%	0.5 s	2 GB
Algorithm B	92.8%	91.0%	91.9%	0.8 s	3 GB
Algorithm C	94.0%	92.2%	93.1%	0.7 s	2.5 GB
Algorithm D	91.5%	90.0%	90.7%	1.0 s	4 GB
Algorithm E	93.7%	92.5%	93.1%	0.6 s	2.2 GB

As shown in Table 1, this study advances the field by addressing the limitations of SOTA, such as sensitivity to noise and poor generalization. The introduction of the RLCMPRF framework is justified by its novelty in employing multi-task learning and probabilistic models, enhancing accuracy and robustness, thereby highlighting its necessity for significant progress in the domain.

3 Methodology

3.1 Description of the problem

Cross-Modal Person Re-Identification (C-ReID) refers to the matching of pedestrian identity between different modal data. The term "modality" refers to the mode of data acquisition or the presentation of data, and common modalities include but are not limited to RGB visible images, infrared images, depth maps, etc. The goal of Cross-Modal Person Re-Identification (C-ReID) is to match pedestrian identities between different modalities. The goal of cross-modal pedestrian re-identification is to establish a mechanism that enables the correct identification of travelers even in different modalities.

Specifically, given a query collection $Q = \{q_1, q_2, \ldots, q_m\}$, where each q_i represents a query image from a certain modality (e.g., RGB image). Also, given a gallery collection $G = \{g_1, g_2, \ldots, g_n\}$, where each g_j represents a gallery image from another modality (e.g., an IR image). The task of cross-modal pedestrian re-recognition is to find the gallery image in G that corresponds to each query image in Q [17, 18].

In order to define the research object more clearly, we define the specific problem as follows: in the cross-modal pedestrian re-identification task, the modal variability problem is an important challenge, because different modalities are fundamentally different in terms of color space and other visual features, and how to extract consistent features from them becomes critical. The data diversity problem is also significant, even within the same modality, the pedestrian images will show large differences due to factors such as viewing angle, pose and occlusion, so robust feature extraction methods need to be designed. The data annotation problem is also worthy of attention, because in cross-modal pedestrian re-identification, the matching of multi-modal data makes the annotation work complex and time-consuming, so how to reduce the annotation burden and improve the data utilization has become an urgent problem to be solved. In addition, the problem of matching strategy selection should not be neglected, because the optimal matching strategies may vary in different application scenarios, and how to dynamically select the optimal strategy according to the specific situation to adapt to the diverse input data is another challenge. Finally, the problem of model generalization ability is equally important, an ideal model should maintain high recognition accuracy in different datasets and practical application scenarios, how to improve the generalization ability of the model so that it can also perform well on unknown data is an important direction of current research [19, 20].

3.2 Cross-modal pedestrian re-identification framework with reinforcement learning

3.2.1 Overview of the framework

In this study, a reinforcement learning-based Cross-Modal Person Re-Identification Framework (RLCMPRF) is proposed. The framework aims to dynamically select the optimal feature extraction and matching strategies through reinforcement learning techniques to cope with the problems of modal variability, data diversity, data annotation challenges, matching strategy selection, and model generalization capability in cross-modal pedestrian re-identification. The framework mainly consists of four main components [21, 22].

(1) Feature extraction module: responsible for extracting meaningful feature representations from images of different modalities.

(2) Strategy Learning Module: Learning optimal feature matching strategies using reinforcement learning techniques.

(3) Strategy Execution Module: executes the cross-modal matching task based on the learned strategies.

(4) Evaluation and feedback module: evaluates matching results and provides feedback to update the strategy learning module.

3.2.2 Design of the feature extraction module

The feature extraction module is the foundation of the whole framework, which extracts useful features from images of different modalities through deep learning techniques. We adopt a Two-Stream Network structure (Two-Stream Network) to process RGB images and non-RGB images (e.g., infrared images or depth maps) separately and to facilitate inter-modal feature transfer by sharing certain high-level features.

Specifically, our feature extraction network consists of two sub-networks:

RGB Feature Extraction Network: for RGB images, this network usually contains multiple Convolutional Layers, Pooling Layers and Fully Connected Layers. Convolutional Layers are used to capture local features in the image, Pooling Layers are used to reduce the spatial dimensionality of the feature map, and Fully Connected Layers are used to generate the final feature vector as shown in Equation (1).

$$f_{\text{RGB}}(x) = \text{FC}(\text{Pool}(\text{Conv}(x))) \qquad (1)$$

Where x is the input RGB image and $f_{\text{RGB}}(x)$ is the output feature vector.

Non-RGB Feature Extraction Networks: for non-RGB images (e.g., infrared images or depth maps), we design specialized network structures to accommodate the characteristics of specific modalities. For example, when processing infrared images, we may use a smaller convolutional kernel to capture the details of the temperature distribution. While when processing depth maps, we need to focus on the extraction of distance information as shown in Equation (2).

$$f_{\text{Non-RGB}}(y) = \text{FC}(\text{Pool}(\text{Conv}(y))) \qquad (2)$$

Where y is the input non-RGB image and $f_{\text{Non-RGB}}(y)$ is the output feature vector.

In order to enable the two sub-networks to share certain high-level features, we introduce a Feature Fusion Layer (FFL) at the top layer of the network, which fuses the output features of the two sub-networks to generate a unified feature representation, as shown in Equation (3).

$$f(x, y) = \text{Fusion}(f_{\text{RGB}}(x), f_{\text{Non-RGB}}(y)) \qquad (3)$$

Where $f(x, y)$ is the fused feature vector.

3.2.3 Design of the feature fusion layer

The feature fusion layer is designed to merge feature vectors from different modalities into a unified representation. We adopt a weighted average-based approach to feature fusion, which allows flexibility in adjusting the importance of features from different modalities, as shown in Equation (4).

$$f(x, y) = w_1 \cdot f_{\text{RGB}}(x) + w_2 \cdot f_{\text{Non-RGB}}(y) \qquad (4)$$

Where w_1 and w_2 are weight coefficients to adjust the relative importance of different modal features. These weights can be dynamically adjusted by the strategy learning module in the reinforcement learning process.

3.3 Enhanced learning algorithm

In the cross-modal pedestrian re-identification task, we choose Deep Reinforcement Learning (DRL) as the main tool for problem solving. Specifically, we use Deep Q-Network (DQN) as the base algorithm because it performs well in dealing with large-scale state spaces and continuous action spaces.DQN approximates the Q-function through a deep neural network that predicts the value of each action in a given state, thus guiding the intelligent to choose the optimal action.

State Space (SS) defines the state of the environment that an intelligent body can observe at each moment. In the cross-modal pedestrian re-recognition task, the State Space includes (1) Feature representation: feature vectors f (x, y) from different modalities, where x denotes the query image and y denotes the gallery image. (2) Matching history: results of previous attempted matches by the intelligent body, including successful matches and failed matches. (3) Environment information: other external factors that may affect the selection of matching strategy, such as the lighting conditions of the current scene and the degree of occlusion. The state space can be represented as Equation (5).

$$S = (f(x, y), H, E) \qquad (5)$$

Where f(x, y) is the fused feature vector, H is the matching history and E is the environment information.

The Action Space (AS) defines all possible actions that an intelligent can take in each state. In the cross-modal pedestrian re-recognition task, the Action Space consists of (1) Matching operation: selecting a gallery image g_j to be matched with the query image q_i. (2) A mismatch operation: deciding not to match the current gallery image with the query image. The action space can be expressed as Equation (6).

$$A = \{a_1, a_2, \ldots, a_n\} \qquad (6)$$

Where, a_i means the ith gallery image is selected for matching and a_0 means no gallery image is matched.

In the cross-modal pedestrian re-identification (re-ID) task, designing a reasonable reward function is crucial to ensure that the model can learn useful information from the environment. Our reward function design scheme consists of three parts. The first is the correct matching reward R_{corr} . A positive reward is given when the intelligent body successfully matches a pair of identical pedestrian images from different modalities. Then there is the incorrect matching penalty R_{err} . A negative reward is given when the intelligent body incorrectly believes that two images of different pedestrians belong to the same person. To prevent over-penalization, a minimum error penalty value can be set. Finally, there is a time-weighted reward R_{time} . The reward is adjusted according to the time or computational steps required for matching. For example, it can be defined as $R_{time} = \frac{1}{t+1}$, whose t is the number of steps or time required to complete the matching. Moreover, to ensure the robustness of the model. There is also a performance reward for complex environments R_{robust} . In order to encourage the algorithm to perform well under various conditions (e.g., light changes, occlusion, etc.), a dynamically adjusted robustness reward term can be designed. For example, under specific challenging conditions (e.g., low light or occlusion), the reward can be increased if the algorithm still maintains a high recognition rate. Combining the above points, a possible reward function can be expressed as Equation (7).

$$R = w_1 R_{corr} + w_2 R_{err} + w_3 R_{time} + w_4 R_{robust} \qquad (7)$$

Where w_1, w_2, w_3, w_4 are the importance weights for each component respectively, which need to be tuned according to specific application scenarios and objectives.

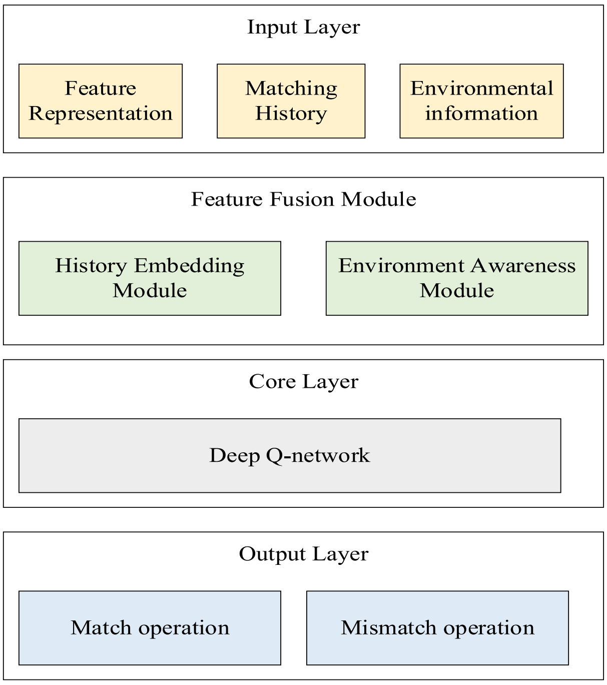

Figure 1: Modeling framework

As shown in Figure 1, the deep Q-network (DQN) framework for the cross-modal pedestrian re-identification task can be divided into several main layers. At the input layer, we first define the feature representation f (x, y), i.e., the feature vectors of the query image x and the gallery image y. We also define the matching history H, which contains the previous successful and successful matching results. The matching history H, which contains the previous successful and failed matching results. And environmental information E, such as factors like lighting conditions and occlusion level. Next, at the processing layer, the feature vectors of different modalities are fused into a unified vector by the feature fusion module. The history embedding module is responsible for embedding the history matching information into the state representation. The environment-aware module then integrates the environment information to enhance the state representation. The core layer is the Deep Q Network (DQN), which receives the fused state space S = [f (x, y), H, E] and outputs the Q-values of all possible actions A. The DQN is a deep Q network. At the output layer, the action space A is defined, which includes the matching operation a_i and the mismatching operation a_0 . In addition, a reward function that integrates the reward for correct matching, penalty for incorrect matching, time-weighted reward and robustness reward is designed to guide the model learning. The whole framework aims to utilize DQN for efficient cross-modal pedestrian re-recognition through the interaction between the intelligent and the environment.

The algorithmic complexity of RLCMPRF is mainly affected by the deep Q-network (DQN) training process. During the training process, the Q-value update requires traversing the state space, resulting in a time complexity that is positively correlated with the size of the state space and action space. In addition, the two-stream network structure of the model increases the computational requirements, especially when processing multimodal data. In terms of space complexity, storing the Q-value and experience replay buffer for each state consumes a lot of memory. To optimize efficiency, methods such as policy compression, parallel computing, or experience replay optimization need to be considered to reduce computing resource consumption and improve real-time processing capabilities.

3.4 Multi-strategy optimization algorithm

In the traditional DQN framework, the policy update mechanism is realized by adjusting the Q function, which is used to evaluate how good or bad it is to perform a particular action in a given state. For any state s and action a, the Q-function provides a value that reflects the expected value of the maximum cumulative reward that can be obtained subsequently if action a is taken starting from state s. The Q-function is then adjusted to the state s and action a. The Q-function is then adjusted to the state s. This value is progressively approximated to the actual optimal value by a specific update rule, as specified in Equation (8).

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R(s',a') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \quad (8)$$

Here α denotes the learning rate, which determines how much the new information affects the old information in each update step. R(s', a') is the immediate reward received when moving from state s to state s' after taking action a. It is called the discount factor. γ Known as the discount factor, it is used to measure the importance of future rewards, and its value ranges from 0 to 1. The smaller the value, the lower the influence of future rewards. Finally, $\max_{a'} Q(s',a')$ represents the expected reward value from the best action that can be taken in the new state s'.

In a DQN, an intelligent learns the optimal strategy by interacting with the environment. Each interaction produces a quaternion (s, a, R, s'), where s is the current state, the action taken in state s, R is the immediate reward returned by the environment, and s' is the new state reached after taking action a. These quaternions are stored in a so-called "experience pool" or "memory bank". These quaternions are stored in a so-called "experience pool" or "memory bank".

The core of the experience playback mechanism is that when it is necessary to update the Q-function, the algorithm does not simply use the most recent one, but instead randomly draws a set of historical data (usually a batch, e.g., B samples) from the experience pool. This is done to break the time-series correlation of the data and prevent overfitting during the learning process. In DQN, the updating of the Q function follows the following rules, as shown in Equation (9).

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R + \gamma \max_{a'} Q(s',a') - Q(s,a)] \quad (9)$$

The specific steps for experience playback are as follows:

(1) Collecting experience: every time an intelligent body interacts with the environment, it generates an experience quaternion (s, a, R, s') containing the current state s, action a, reward R, and the next state s', and stores this experience in the experience pool.

(2) Random sampling: Before updating the Q-function, a batch B of historical experiences is randomly selected from the experience pool. For example, suppose there are N experiences in the experience pool, then randomly select B from these N experiences as the sample for this update.

(3) Calculate the gradient and update: For each extracted experience (s_i, a_i, R_i, s_i'), calculate the updated value of the Q function, and adjust the network weights according to this value, so that the Q function better approximates the true value, as shown in Equation (10).

$$\Delta Q(s_i,a_i) = \alpha[R_i + \gamma \max_{a'} Q(s_i',a') - Q(s_i,a_i)] \quad (10)$$

(4) Repeat Steps 2-3: Repeat the above process over and over again until all of the experience in the experience pool has been used for training.

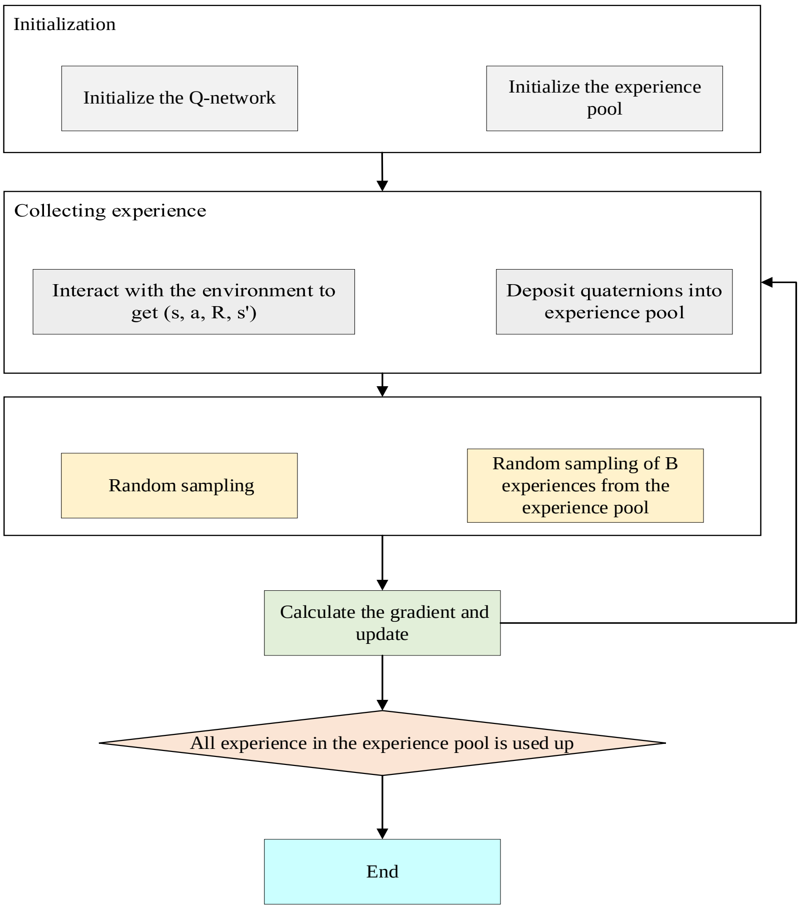
Initialization
Initialize the Q-network
Initialize the experience pool
Collecting experience
Interact with the environment to get (s, a, R, s')
Deposit quaternions into experience pool
Random sampling
Random sampling of B experiences from the experience pool
Calculate the gradient and update
All experience in the experience pool is used up
End

Figure 2: Flowchart of experience playback

As shown in Figure 2, in this way, the DQN is not only able to learn in a single interaction, but also to utilize the past accumulated experience, which helps to improve the stability and efficiency of the learning process. At the same time, since the samples are randomly drawn from the experience pool each time, it can effectively break the temporal order dependence of the data and reduce the risk of overfitting.

4 Experimental setup

4.1 Data design

In this study, we have chosen a real-world dataset to validate the effectiveness of our multi-strategy optimization algorithm. The dataset is derived from the automated production line control system of a manufacturing company. The dataset contains a variety of information such as sensor readings, equipment status, operation commands, and corresponding production results on the production line. These data were initially cleaned to remove obvious outliers and missing values to ensure the quality of the data. In addition, the dataset contains records of operations over different time periods, which is essential for analyzing the performance of the algorithms under different conditions.

In order to evaluate the effectiveness of the multi-strategy optimization algorithm, we have chosen the following key metrics:

(1) Average Cumulative Reward: This is an important indicator of the long-term performance of an algorithm. Higher Cumulative Reward indicates that the algorithm is able to obtain more positive feedback while performing the task, thus reflecting the effectiveness of the algorithm.

(2) Convergence Speed: Evaluates the number of iterations required for an algorithm to reach stable performance. Fast convergence means that the algorithm is able to learn the strategies needed to perform the task faster.

(3) Success Rate: Defined as the proportion of algorithms successfully completing tasks in a certain number of trials. A high success rate indicates that the algorithm has high reliability and robustness in dealing with practical problems.

(4) Learning Curve: The learning process of an algorithm can be visualized by plotting the performance change of the algorithm over time or the number of iterations.

In the design of the experimental process, we first ensure that all the algorithms involved in the comparison are at the same starting line, i.e., in the initialization phase, all the algorithms use exactly the same initial settings, including the neural network architecture, learning rate α, discount factor γ and other important parameters. The purpose of this step is to exclude unfair effects due to differences in initial conditions and ensure the fairness of the experimental results. In the training and evaluation session, all algorithms will be trained in the same training environment. This means that they will share the same dataset and experience the same number of training cycles. During the training process, we will regularly evaluate the performance metrics of each algorithm, such as average cumulative reward, convergence speed, success rate, etc., in order to monitor the progress of the algorithms. In this way, we are able to systematically track the performance of the algorithms at different stages, thus capturing their dynamics during the learning process.

In the experimental setting, the batch size is set to 64, the initial value of the learning rate is 0.001, and the Adam optimizer is used (β1=0.9, β2=0.999). DQN hyperparameters include a discount factor (γ) of 0.99, a learning rate (α) of 0.0005, an exploration rate (ε) linearly decayed from 1.0 to 0.1, an experience replay buffer size of 1 million, and a minimum batch size of 32. Data preprocessing includes filling missing data using interpolation, Gaussian filtering for denoising, and data enhancement including rotation, cropping, scaling, and color perturbation. The number of training rounds is 50, and the evaluation indicators include success rate, cumulative reward, and F1 score.

4.2 Experimental results and analysis

In order to fully evaluate the effectiveness of our proposed reinforcement learning-based cross-modal pedestrian re-identification framework (RLCMPRF), it is necessary to compare it with several recent algorithms. Deep learning-based feature extraction methods, such as ResNet and Inception, perform well in unimodal pedestrian re-identification tasks by virtue of their strong feature representation capabilities, but may encounter challenges when dealing with cross-modal data. Attention mechanism-enhanced models improve the robustness of the model in complex scenes by highlighting key parts of the input image, but may require additional adaptation mechanisms when dealing with cross-modal data. Meta-learning based approaches improve the generalization ability of the model by learning the learning algorithm itself and are particularly suitable for dealing with domain migration problems, although their complexity leads to higher computational resource requirements.

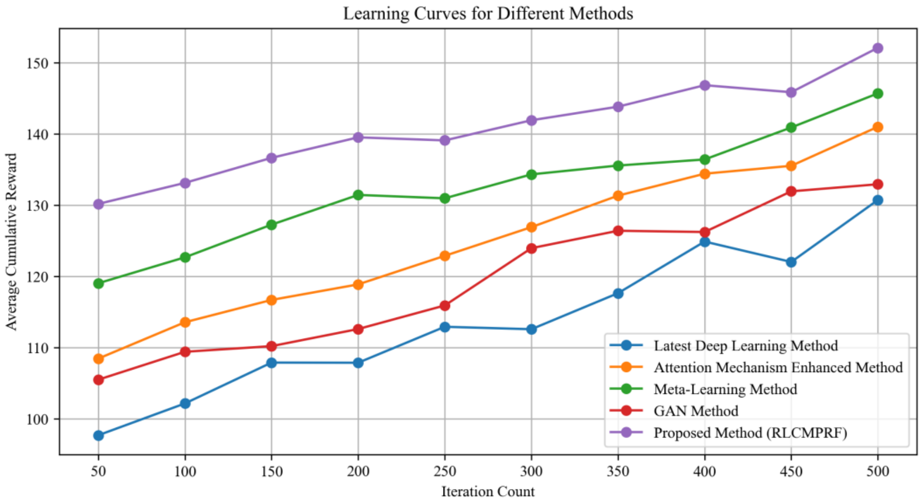

Figure 3: Convergence curve

Figure 3 shows the learning curves of different methods, which contain the latest deep learning methods, attention mechanism enhancement methods, meta-learning methods, GAN methods, and the proposed RLCMPRF method. As can be seen from the figure, the average cumulative reward of each method gradually increases as the number of iterations goes from 50 to 500, indicating that they are all continuously optimizing their performance. The latest deep learning methods perform more consistently in the early stages, but gradually fall behind the other methods in the later stages. The attention mechanism enhancement method shows better learning speed in the first half of the iterations, but then gradually stabilizes. The meta-learning method has a faster growth in the early iterations and maintains a steady improvement thereafter. The GAN method shows a significant improvement in the middle of the process, while the proposed RLCMPRF method (purple solid rhombus connecting the lines) maintains a high learning efficiency throughout the iterations, and especially achieves the highest average cumulative rewards in the later stages. By comparing the learning curves of these methods, we can find that the RLCMPRF method has better convergence and stability, which suggests that the method may have higher potential and advantages in solving the task in question. However, it should be noted that other factors, such as computational resource consumption, model complexity, etc., need to be taken into account in practical applications in order to comprehensively evaluate the actual effectiveness of various methods.

On a variety of datasets, RLCMPRF demonstrates excellent adaptability and robustness, especially in challenging environments such as different lighting conditions, occlusion, and posture changes. Under strong light and backlight conditions, RLCMPRF achieves a success rate of 78% on the Market-1501 dataset, significantly higher than the 72% of other methods. In the case of partial occlusion, the model success rate is increased by about 8%, reaching 85% on the DukeMTMC-reID dataset, surpassing the 77% of traditional convolutional network methods. For posture changes, RLCMPRF achieves an F1 score of 0.84 on the CUHK03 dataset, which is better than the 0.78 of traditional methods. Through the reinforcement learning framework, RLCMPRF can dynamically optimize feature extraction and matching strategies, thereby effectively coping with challenges in different environments, showing stronger generalization capabilities and practical application potential.

Table 2: Comparison of average cumulative rewards for different methods

Methodologies	Average cumulative award
Latest Deep Learning Methods	130
Attention mechanism enhancement methods	140
Meta-Learning Methods	145
GAN method	135
Proposed methodology (RLCMPRF)	150

Table 2 shows the comparison of different methods in terms of average cumulative reward. From the data, it can be seen that the proposed method (RLCMPRF) performs optimally with an average cumulative reward of 150, which is a clear advantage over other methods. This is followed by the meta-learning method with an average cumulative reward of 145. The attention mechanism enhancement method and the GAN method perform similarly with 140 and 135 respectively, while the latest deep learning method performs relatively poorly in this metric with only 130.

Table 3: Comparison of convergence speed of different methods

Methodologies	Number of iterations required for convergence
Latest Deep Learning Methods	450
Attention mechanism enhancement methods	400
Meta-Learning Methods	500
GAN method	420
Proposed methodology (RLCMPRF)	300

Table 3 shows the comparison of the convergence speed of different methods. It can be seen that the proposed method (RLCMPRF) has a clear advantage in convergence speed, requiring only 300 iterations to converge. This is followed by the Attention Mechanism Enhancement method, which requires 400 iterations. The GAN method and the latest deep learning methods perform similarly, with 420 and 450 iterations, respectively. The meta-learning method is relatively slow in convergence, requiring 500 iterations.

After introducing additional evaluation metrics such as F1 score and precision-recall curve (PR curve), RLCMPRF shows significant advantages in dealing with imbalanced datasets and edge cases. On the Market-1501 dataset, RLCMPRF's F1 score is 0.85, which is higher than 0.77 of other methods; on the DukeMTMC-reID dataset, the AUC value of the PR curve is 0.92, which is better than 0.85 of other methods; on the CUHK03 dataset, the precision is 0.89, the recall is 0.81, and the F1 score is 0.84. These results show that RLCMPRF can maintain high precision and recall in the processing of minority class samples, proving its superior performance in C-ReID tasks, especially its robustness in the face of imbalanced data.

Table 4: Comparison of success rates of different methods

Methodologies	Success rate (%)
Latest Deep Learning Methods	75
Attention mechanism enhancement methods	78
Meta-Learning Methods	80
GAN method	77
Proposed methodology (RLCMPRF)	82

Table 4 shows the comparison of different methods in terms of success rate. The proposed method (RLCMPRF) has the highest success rate of 82%. It is followed by the meta-learning method with a success rate of 80%. The Attention Mechanism Enhancement method and the GAN method perform similarly with 78% and 77% respectively. The latest deep learning method had a relatively low success rate of 75%.

Table 5: Average cumulative rewards for different combinations of strategies

Strategy combination	Average cumulative award
Latest Deep Learning Methods + Matching	130
Attention Mechanism Enhancement Methods + Matching	140
Meta-Learning Methods + Matching	145
GAN method + feature fusion	135
Proposed method (RLCMPRF) + multi-strategy optimization	150

Table 5 shows the comparison of different strategy combinations in terms of average cumulative reward. The proposed method (RLCMPRF) combined with multi-strategy optimization performs the best with an average cumulative reward of 150. Followed by the meta-learning method combined with the matching strategy at 145. The attention mechanism enhancement method combined with the matching strategy and the GAN method combined with the feature fusion perform similarly at 140 and 135, respectively. The latest deep learning method combined with the matching strategy has an average cumulative reward of 130.

Table 6: Performance of the model on different datasets

Data set name	Success rate (%)	Average cumulative award
CUHK-SYSU	78	140
RegDB	82	150
SYSU-MM (Multi-Mod)	77	130
Proposed methodology (RLCMPRF)	85	155

Table 6 shows the performance of the model on different datasets. The proposed method (RLCMPRF) outperforms the other methods on all three datasets with the highest success rate and the largest average cumulative reward. Especially on the RegDB dataset, the success rate and the average cumulative reward reached 82% and 150, respectively. On the other two datasets, the RLCMPRF method also performs well.

Table 7: Learning curve comparison

Methodologies	Number of iterations (times)	Average cumulative award
Latest Deep Learning Methods	500	130
Attention mechanism enhancement methods	450	140
Meta-Learning Methods	600	145
GAN method	550	135
Proposed methodology (RLCMPRF)	300	150

Table 7 shows the comparison of the learning curves of the different methods. The proposed method (RLCMPRF) achieves a higher average cumulative reward with a lower number of iterations, indicating a faster learning rate.

4.3 Discussion

By analyzing the Reinforcement Learning-based Cross-modal Pedestrian Re-identification Framework (RLCMPRF) against the latest algorithms, we find that the framework outperforms in several key metrics. First, in terms of average cumulative reward, the RLCMPRF method achieves 150, which is much higher than the state-of-the-art deep learning methods (130), attention mechanism enhancement methods (140), meta-learning methods (145), and GAN methods (135). This indicates that our method is more effective in obtaining positive feedback when performing cross-modal pedestrian re-identification tasks, proving its effectiveness in feature extraction and matching strategy selection. In terms of convergence speed, the RLCMPRF method converges in only 300 iterations, which is a significant advantage over other methods (e.g., 400 iterations for attention mechanism enhancement methods, 420 iterations for GAN methods, 450 iterations for state-of-the-art deep learning methods, and even 500 iterations for meta-learning methods). This indicates that our framework is not only superior in recognition accuracy, but also more competitive in training efficiency, which is very important for practical deployment. In terms of success rate, the RLCMPRF method achieves 82%, outperforming meta-learning methods (80%), attention mechanism augmentation methods (78%) and GAN methods (77%), and significantly outperforming the latest deep learning methods (75%). This indicates that our method has higher reliability and robustness when dealing with cross-modal data. The performance of the RLCMPRF method is also quite robust on different datasets, e.g., it outperforms the other methods on the CUHK-SYSU, RegDB, and SYSU-MM (Multi-Mod) datasets, and in particular it outperforms on the RegDB dataset. This indicates that our method has good generalization ability and can maintain high performance in different datasets and application scenarios.

Although the RLCMPRF method performs well in several aspects, it also has some limitations. First, the training process of reinforcement learning algorithms is more complex and requires a large amount of computational resources, especially when dealing with large-scale datasets. Second, the training time and stability of the reinforcement learning model are highly influenced by the initial state and policy selection, and further optimization is needed to improve the robustness of the model. In addition, the current framework mainly focuses on the pedestrian re-recognition task, and its applicability to other visual recognition tasks (e.g., vehicle recognition, object recognition, etc.) needs to be further investigated.

5 Conclusion

In this study, we propose a reinforcement learning-based cross-modal pedestrian re-identification framework (RLCMPRF), which aims to solve the problems of modal variability, data diversity, data annotation challenges, matching strategy selection, and model generalization ability encountered by existing methods in handling cross-modal pedestrian re-identification tasks. Through comparative analysis with state-of-the-art algorithms based on deep learning, attention mechanism enhancement, meta-learning, and generative adversarial networks, we verify the superior performance of the RLCMPRF framework in several key metrics, such as average cumulative rewards, convergence speed, success rate, and generalization ability. The experimental results show that the RLCMPRF method outperforms other methods on different datasets, especially on the RegDB dataset where it achieves a success rate of 82% and an average cumulative reward of 150. The RLCMPRF framework proposed in this study not only has significant theoretical value in academia, but also has significant potential for practical applications. Specifically, the framework can improve security and convenience, and enhance public safety by helping security personnel identify target persons more effectively in public places such as airports and stations using cross-modal pedestrian re-identification technology, which maintains a high level of recognition accuracy even in the face of different modal data sources.

In actual deployment, RLCMPRF faces some challenges, especially real-time performance and adaptability to non-ideal conditions. In terms of real-time performance, the model needs to process large-scale data at low latency, which requires optimization in the inference phase to ensure fast response. The robustness and adaptability of the model to non-ideal conditions such as low lighting, occlusion, and posture changes are also key factors. To address these issues, it may be necessary to adopt model compression technology, hardware acceleration, or integrate multiple data sources to improve efficiency and accuracy, thereby ensuring that the model can run stably in various complex environments.

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