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AI Methods and Applications in 3D Technologies

Proceedings of 3DWCAI 2023

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Preface

This book is Volume I of the Proceedings of the Second World Conference on Intelligent and 3D Technologies (WCI3DT2023): *AI Methods and Applications in 3D Technologies.*

The conference took part during May 26–28, 2023, in Shanghai, China.

The aim of WCI3DT 2023 was to provide a wide forum to academicians and practitioners where they to present latest scientific results and to exchange ideas in the area of Artificial Intelligence and Deep Learning and their applications in augmented reality and 3D technologies. The conference organizers were focused on the establishment of an effective platform for all participants to introduce their work to scientists, engineers, and students from all over the world.

After reviewing, 61 papers were accepted for presentation and publication in the conference proceedings, of which 30 are in this volume. The selected works present contemporary research works aimed at the area of multidimensional signal processing, and based on contemporary methods and applications in 3D technologies, such as the multi-terrain motion control method for quadruped robot based on reinforcement learning, the method for detection of basal units beneath the Antarctic ice, the study on the applications of AI algorithms in medicine, the creation of an intelligent recommendation algorithm for music website, the creation of a 3D scene simulation optimization model, a special approach for gesture recognition in complex background, various contemporary applications based on AI and DL algorithms, and other interesting ideas. The chapters are arranged in three groups, which cover different parts of the related scientific areas:

- AI-Based Approaches (11 chapters);
- 3D Technologies and DL (9 chapters);
- Intelligent Methods and Applications (10 chapters).

In memory of Prof. Dr. Roumen Kountchev, Dr. Sc., *Best Paper Award* was established by the Organizing Committee. Due to the high number of very good works, the selection was extremely difficult. Two papers were selected as "*winner paper*", and published in this volume as Chap. 1 and Chap. 2, respectively.

The winner papers are

"Extended Prototypical Network for Few-shot Learning", with authors: Jingjing Zhang, Lujie Cui, Wenfeng Wang, and Lalit Mohan Patnaik;

and

"Low Carbon Scheduling of Thermal Power Unit Thermal Storage Capacity Based on Particle Swarm Optimization", with authors: Wenbin Cao, Mingkai Wang, Bo Han, Qi Chai, Hongtao Li, and Ying Liu.

The book editors express their special thanks to IRNet International Academic Communication Center who organized this conference in correspondence with their dedication to build platforms for scholars and researchers for better knowledge sharing, together with providing full-scale conference services that meet the standards of the renowned publishing organizations.

We also thank Prof. Lakhmi Jain (Honorary chair), Prof. Wenfeng Wang, Prof. Srikanta Patnaik, Prof. Gang Sun, and Prof. Xudong Jiang (General chairs), Dr. Yonghang Tai, Dr. Shoulin Yin, and Prof. Hang Li (Organizing chairs), and S. R. Dr. Roumiana Kountcheva (International advisory chair).

The editors express their warmest thanks to the excellent Springer team for making this book possible.

Sofia, Bulgaria	Prof. Dr. Roumen Kountchev
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Shanghai, China	Prof. Dr. Wenfeng Wang
Sofia, Bulgaria	S. R. Dr. Roumiana Kountcheva
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AI-Based Approaches

Chapter 1
Extended Prototypical Network for Few-Shot Learning

Jingjing Zhang, Lujie Cui, Wenfeng Wang, and Lalit Mohan Patnaik

Abstract This paper proposes a learning method based on extended distance for unsupervised meta-learning. Compared with previous algorithms, the network can also learn new classes and correctly classify them, and each class only requires a few shots for training. Among them, extension distance emerged as a new distance measurement method, which has obvious advantages over the previous Euclidean distance. This paper compares it with the prototypical network based on Euclidean distance and compares and analyzes the experimental results, the experiment that works best is the Miniimagenet dataset which improves accuracy by about 2.36%. The meta-learning method based on metric space is further explored, and experiments are carried out on three data sets and achieved good experimental results on MNIST, miniimagenet, and omniglot data sets.

1.1 Introduction

Extenics is a new discipline founded by Chinese scholars headed by Professor CAI Wen. It utilizes formal models to study the possibility of expansion of things and methods of exploration and innovation, primarily for dealing with contradictions [1]. The basic element theory puts forward the basic element that describes events, matters, and relation elements—"event elements", "matter elements" and "relation elements". In this paper, we regard each class as a matter element, and classes should have corresponding features, and the features also correspond to values, which usually expresses in extensions as (N, C, V). Extension distance mainly describes the distance relationship between point and interval. Furthermore, we can refer to the construction of the elementary correlation function of interval side distance based

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on area distance [2]. According to current studies, three metric-based meta-learning models are Matching Net, Proto Net, and relation Net [3]. The previous Siamese Network is a two-path Neural Network [4]. During training, different pairs of samples are constructed by combination and input into the Network for training. At the top layer, the distance of sample pairs is used to judge whether they belong to the same class and generate corresponding probability distribution. In the prediction stage, the twin network processes each sample pair between the test sample and the support set, and the ultimate prediction result is the category with the highest probability on the support set [5]. Compared with twin networks, Match Network constructs different encoders for the support set and batch set, and the output of the final classifier is the weighted sum of predicted values between the support set and the query set [6]. It can generate labels for unknown categories without changing the network model, and its main innovation is reflected in the modeling process and training process.

Problems existing in metric-based meta-learning: the core of matrix operation learning lies in the setting of the loss function, and the matrix operation is large [7]; High requirements on data sets, in some newly proposed loss functions, may increase a lot in face data sets, but the effect on other tasks will be worse. And in this paper, we aim to ease the problem of large computation of the meta-learning matrix and improve the accuracy of classifications [8]. And we mainly used K-means for clustering division.

The purpose of this study is to apply theoretical knowledge to expansion, study the meta learning algorithm based on metric space optimization problem, formalize samples and quantitative features, and establish matter element model [9], so that things can be displayed more intuitively and formally for analysis and conversion. Another research focus of this paper is to design a suitable extension distance to measure the distance between samples, and then conduct training under the model structure, so that the training and testing effect can achieve the optimal [10]. It is beneficial to improve the effect of classification and recognition by introducing the theory knowledge of extensions and studying more distance measurement methods. We compare the improved prototypical network using extension distance with the prior prototypical network using Euclidean distance and get good experimental results on three data sets. Firstly, the input data requires to be mapped, and then the unlabeled data set is classified by clustering partition through K-means algorithms. Afterwards, by comparing the query dataset and interval, the closer the distance, the higher the similarity.

1.2 Two Stages of Meta-Learning

Stage 1: Training Train Tasks

Meta-learning mainly consists of two stages, the first stage is the inner cycle training task training; The second stage is the outer loop test task training. The partitioning of the data set remains the same, except that the training set also includes the training set and the test set, and the test set is the same. Through the support set training, the model parameters for each sub-task are trained respectively. The query sets of different subtasks are then used to test the performance separately and calculate the loss between the predicted and true values. Finally, the gradient descent method is used to update parameters, so as to find the optimal super-parameter setting. The training process of the training task in stage 1 can be shown in the Fig. 1.1.

There are N tasks sampled during the training task stage as shown in the Fig. 1.1, and each training support task set can be represented as $\{(x_1^{ks}, y_1^{ks}), (x_2^{ks}, y_2^{ks}), \ldots, (x_n^{ks}, y_n^{ks})\}, k = 1, 2, \ldots, N$, n represents the number of samples in the support set. Each training query task set can be represented as $\left\{\left(x_1^{kq}, y_1^{kq}\right), \left(x_2^{kq}, y_2^{kq}\right), \ldots, \left(x_m^{kq}, y_m^{kq}\right)\right\}, k = 1, 2, \ldots, N$, m represents the number of samples in the query set. Wherein φ indicates the hyperparameter to be set, θ represents the parameters of the neural network to be trained. The purpose of meta learning is to enable function f_{φ,θ_k} to automatically train $F_{\theta_k^*}$ in training tasks, then utilizing the prior knowledge of F_{φ^*,θ_k^*} to train the parameters in the model for

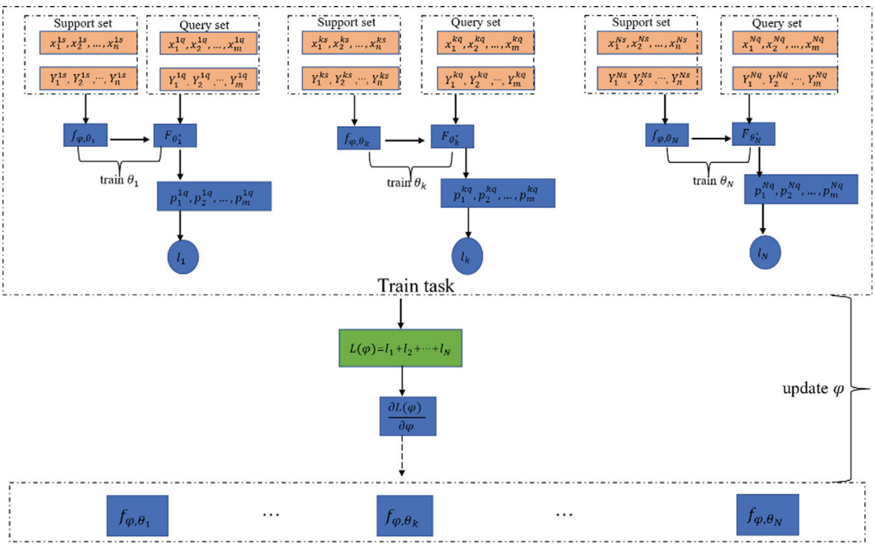

Fig. 1.1 Meta-learning train tasks training parameters

specific tasks in testing tasks。Where $\{p_1^{kq}, p_2^{kq}, \ldots, p_m^{kq}\}$ represents the test label value corresponding to the trained θ_k^* in the training test set sample.

The box above shows the update parameter θ, and the updating process can be specifically described as: the training parameter θ of the support set of the training task, and then the query set in the training task updates the parameter θ, and finally, the partial derivative with respect to φ is obtained:

Stage 2: Test Tasks Update Parameters

The test task is similar to the machine learning process, and the test set is also divided into training set and testing set. The phase 1 training task is to find good parameter Settings and perform the task better in a specific test task. This stage is mainly divided into training data and test data. The training data is mainly responsible for training the parameter θ, and the test data is updated with the known parameter changes, and finally, the output is obtained. In the test task, the parameter update process is shown in Fig. 1.2:

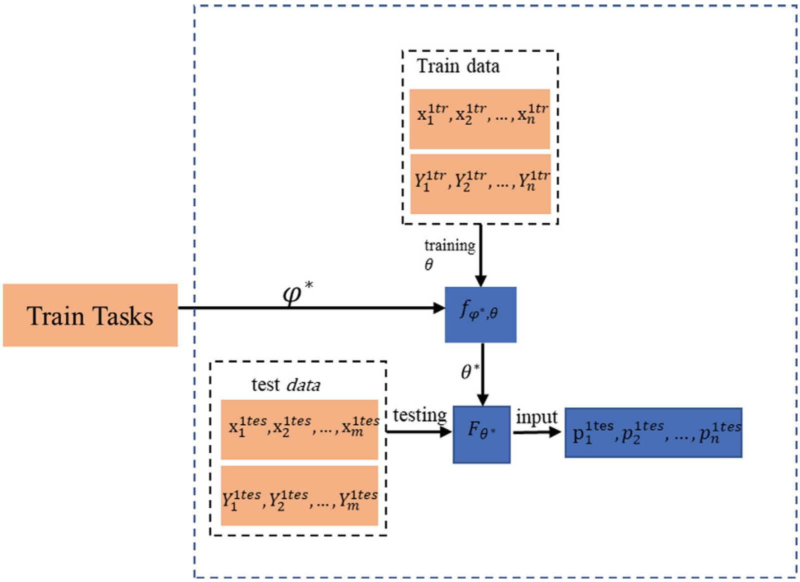

Fig. 1.2 Meta-learning test tasks updates parameters

1.3 Research on Unsupervised Meta-Learning in Metric Space

Notation

The concept is established to formalize the description of the matter element, event element, and relation element 11. They are the logical cells of extensions and are collectively referred to as primitives. This paper mainly introduces the concept of matter elements.

Definition 2.1 With matter O_m as the objects, c_m as the features, O_m as the ordered triad of value v_m about c_m:

$$M = (O_m, c_m, v_m) \tag{1.1}$$

As the basic element of describing matters, they are collectively called one-dimensional matter elements, O_m, c_m, v_m are the three elements. $c_m$andv_m construct the dualistic group of (c_m, v_m) as the feature elements.

Definition 2.2 Let x be any point on the real axis, X = < a, b > is any interval on the real field, called

$$\rho(x, X) = \left|x - \frac{a+b}{2}\right| - \frac{b-a}{2} \tag{1.2}$$

The above formula is the extension distance of the point x and the interval X = < a, b > , where X can be an open, closed, or half-open and half-closed interval.

For any point x_0 in the real axis, there is:

$$\rho(x, X) = \left|x_0 - \frac{a+b}{2}\right| - \frac{b-a}{2} = \begin{cases} a - x_0, x_0 \le \frac{a+b}{2} \\ x_0 - b, x_0 \ge \frac{a+b}{2} \end{cases} \tag{1.3}$$

Extension Distance and Establish the Matter-Element Model

To describe the difference between classes, the distance relationship between the point and interval is defined before establishing the correlation function, which is called extension distance.

Properties 2.1 A given interval $X =< a, b >$, so

(1) The sufficient and necessary conditions for the point $x \in X$ and x $\neq$ a, b are $\rho(x, X) < 0$;

(2) The sufficient and necessary conditions for the point $x \notin X$ and $x \neq$ a, b are $\rho(x, X) > 0$;
(3) The sufficient and necessary conditions for the point x = a or x = b are $\rho(x, X) = 0$;

Step 1: Establish the corresponding matter-element model according to the features or dimensions of examples:

$$X = (x, I, a_i(x)) = \begin{bmatrix} x & I_1 & a_1(x) \\ & I_2 & a_2(x) \\ & \cdots & \cdots \\ & I_m & a_m(x) \end{bmatrix} \tag{1.4}$$

Where $a_j(x)$ the value of jth feature I_j of matter-element X, j = 1,2…,m.

Step 2: Let N dimension vectors $x_j(j = 1, 2, \ldots, N)$ divided into N groups $\mathrm{v}_1, \mathrm{v}_2, \ldots, \mathrm{v}_n$, suppose there are k_1 group from class v_1,…, and there are N_n from class v_n. And find the center of each group to minimize the value function of similarity (or distance) features, where the distance is measured by extension distance.

Step 3: Calculate the central matter element of this class:

$$\mathrm{C} = (\mathrm{C_i}, \mathrm{I}, \mathrm{c_i}(\mathrm{w_i})) = \begin{bmatrix} \mathrm{C_i} & \mathrm{I_1} & \mathrm{c_1}(\mathrm{w_1}) \\ & \mathrm{I_2} & \mathrm{c_2}(\mathrm{w_2}) \\ & \cdots & \cdots \\ & \mathrm{I_m} & \mathrm{c_m}(\mathrm{w_i}) \end{bmatrix} \tag{1.5}$$

Among them $c_i(\mathrm{w}_i) = \frac{\sum_{h=1}^{N_i} a_j(x_h)}{N_i}$, $j = 1, 2, \ldots, m; i = 1, 2, .., n$.

Minimum value of corresponding feature of matter-element $\mathrm{v}_j^l = \min\limits_{h \in N_i}\{a_j(x_h)\}$, minimum value of corresponding feature of matter-element $\mathrm{v}_j^l = \max\limits_{h \in N_i}\{a_j(x_h)\}$, joint domain for $V_j(\mathrm{w}_i) = \left[\mathrm{v}_j^l, \mathrm{v}_j^l\right]$, j = 1,2,..,m;i = 1,2,…,n. Then the matter-element model of this class can be constructed as:

$$W = (\mathrm{w}_i, I, V) = \begin{bmatrix} w_i & I_1 & V_1(\mathrm{w}_1) \\ & I_2 & V_2(\mathrm{w}_2) \\ & \cdots & \cdots \\ & I_m & V_m(\mathrm{w}_i) \end{bmatrix} \tag{1.6}$$

In this paper, we define the extension distance function is:

$$d(x, \mathrm{w}_i) = \sum_{j=1}^{m} [\frac{(a_j(x) - c_j(\mathrm{w}_i))^2 - (\frac{\mathrm{v}_j^u - \mathrm{v}_j^l}{2})^2}{2}] \tag{1.7}$$

Which satisfies the properties 2.1.

Based Metric Space Meta-Learning Model

The prototypical network is mainly based on the embedding space after nonlinear mapping, clustering each class of the embedding space to gain the mean value of samples as the prototype of every class. And we use a neural network to learn a nonlinear mapping of the input into the embedding space. Classification is mainly about comparing the distance between the query point and the nearest neighbor prototype. First, the data is mapped to an embedded space, then the prototype network can identify new categories that have never been seen during training, each requiring very little information from the support set12. Compared to the Euclidean distance to measure the similarity of query set and prototype, we want to further optimize the Prototypical Networks. In the clustering automatically construct task for unsupervised (CACTUs) [13] prototypical networks for classifications, there gives a support set of m labeled examples and a query set s_q, y_m is the one-hot labels which get from CACTUs:

$S_k = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m), y_i \in \{1, 2, \ldots, K\}$ is the corresponding set. S_k denotes the set of examples labeled with class k. In this case, the relationship between embedded query points and the class prototype is:

$$p_\phi(y = k|x_i) \propto \exp(-d(f_\varnothing(x_i), c_k)) \tag{1.8}$$

In the embedding space, we can calculate the prototype of the k-th class:

$$c_k = \frac{1}{|S_k|} \sum_{(x_i, y_i) \in S_k} f_\phi(x_i) \tag{1.9}$$

c_k is the prototype, f_ϕ is an embedding function;

Given a distance function, there we use extension distance for prototypical networks to choose the relatively closer prototype, which is the extension distance to produce a distribution over class for a query point x based on a softmax:

$$p_\phi(y = k|x_i) = \frac{\exp(-d(f_\phi(x_i), \mathrm{w}_i))}{\sum_{k'} exp(-d(f_\phi(x_i), \mathrm{w}_i))} \tag{1.10}$$

Where we define an extension distance:

$$d(x, \mathrm{w}_i) = \sum_{j=1}^{m} \left[\frac{\left(a_j(x) - c_j(\mathrm{w}_i)\right)^2 - \left(\frac{\mathrm{v}_j^u - \mathrm{v}_j^l}{2}\right)^2}{2} \right] \tag{1.11}$$

Table 1.1 Unsupervised extension prototypical network algorithm

Algorithm 1 Extension Prototypical Network for Few-shot Learning

1: Require: Given a dataset D and clustering partition get $S_k = \{(x_i, y_i)\ \ y_i \in \{1,2,\ldots,K\}$
2: Random samples $(\{1,2,\ldots,K\}, S_k)$,S_Q is the query set.
Compute the class prototype, c_k is the prototype, f_ϕ is an embedding function:

$$c_k = \frac{1}{|S_k|} \sum_{(x_i,y_i)\in S_k} f_\phi(x_i)$$

3: Compute the probability of query point which belongs to one of the prototypes through Extension distance:

$$p_\phi(y = k|x_i) = \frac{\exp(-d(f_\phi(x_i), w_i))}{\sum_{k'} exp(-d(f_\phi(x_i), w_i))}$$

4: $J \leftarrow 0$
$for\ j\ in\ \{1,\ldots,S_k\}\ do$
$for\ (x,y)\ in\ S_Q\ do$

$$J \leftarrow J + \frac{1}{S_k S_Q}\ (-log p_\phi(y = k|x_i))$$

Finally, we can calculate the loss function we can apply

$$J(\phi) = -log p_\phi(y = k|x_i) =$$

$$d\big(f_\varnothing(x_i), \mathrm{w}_k\big) + log \sum_{k'} \exp\big(-d\big(f_\varnothing(x_i), \mathrm{w}_{k'}\big)\big)$$

The above is the process in which we combine the entropy weight method to improve the prototypical network. The algorithm is shown in Table 1.1:

1.4 Experiments

Unsupervised Learning for Prototypical Network on MNIST

The MNIST dataset is relatively simple compared with the other two datasets, so the classification accuracy is relatively higher than the other two datasets under the same N-way and K-shot conditions. Extension distance can improve generalization ability, in order to prove this, we carried out the following experiment. As shown in the following figure, the comparison about the prototypical network is under two different metric distances. As shown in Table 1.2, for 5-way and 1-shot, we statistic experimental results and compare Extension distance and Euclidean distance, the Extension distance higher by 1.3% than Euclidean distance. And for 5way-5shot, we can get an accuracy of about 92.38% which is higher than before and the accuracy of Euclidean is 92.26%. What can be further discussed is that although the MNIST data set is simple, our experimental effect is better than before under the condition of 20way and 1shot, but the accuracy is not high as shown in Table 1.2.

Unsupervised Learning for Prototypical Network on Omniglot

As shown in Fig. 1.3, applying Euclidean Distance in the prototype network has a higher training loss than the extension distance at the beginning, although the global trend is similar to the extension Distance. It reflects our method is relatively stable. According to Fig. 1.4, we can see that the situation of train loss is the same as in Fig. 1.3. The accuracy of val accuracy is higher than the prototype network of Euclidean Distance in both the beginning and the end stages. As shown in Fig. 1.5, the initial extended distance in the prototype network has a higher training loss. To observe the accuracy of validation more clearly, as shown in Fig. 1.6, the method of extension is significantly higher than that of Euclidean Distance. As depicted in Table 1.3, we statistic three groups of experiments and the corresponding results of the prototype network that using extension distance are 64.77, 79.32 and 41.99%, while the corresponding results of the prototype network using Euclidean distance are 64.71, 78.99 and 41.74%, respectively.

Unsupervised Learning for Prototypical Network on Miniimagenet

Since this data is more difficult to classification than the other two data sets, we adopt three ways to construct the task for N-way K-shot here, for 5-way,20-shot, we take the cluster number is $k = 50$, the partition number is $p = 10$; And for 5-way, 5-shot, we take the cluster number is $k = 100$, the partition number is $p = 50$; Finally, for 5-way,2-shot, we take the cluster number is $k = 500$, the partition number is $p = 100$. The comparison results are shown in Figs. 1.7 and 1.8. Surprisingly, the effect is better than the above data set. As depicted in Table 1.4, we statistic two groups of experiments and the corresponding results of the prototype network that using extension distance are 50.37 and 41.62%, while the corresponding results of the prototype network using Euclidean distance are 48.92 and 40.37%, respectively. As depicted in Table 1.5, by setting the number of clusters to $k = 500$, it show better classification when the data set is more difficult.

Table 1.2 Based on different metric distance of few-shot classification accuracies on Mnist; We all take the cluster number is $k = 50$, partition number is $p = 10$

Model	Dist	5-way Acc		20-wayAcc
		1-shot	5-shot	1-shot
Prototypical network	Extension	85.17%(↑1.3)	92.38% (↑0.12)	37.92%(↑0.07)
Prototypical network	Euclidean	83.87%%	92.26%	37.85%

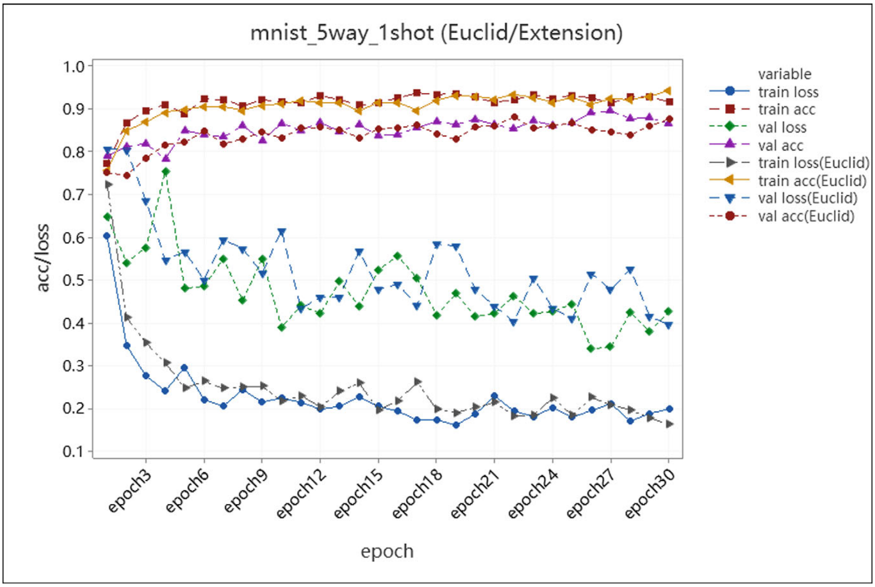

Fig. 1.3 Comparison of two distance ways for the prototypical network with the same MNIST dataset 5-way 1-shot

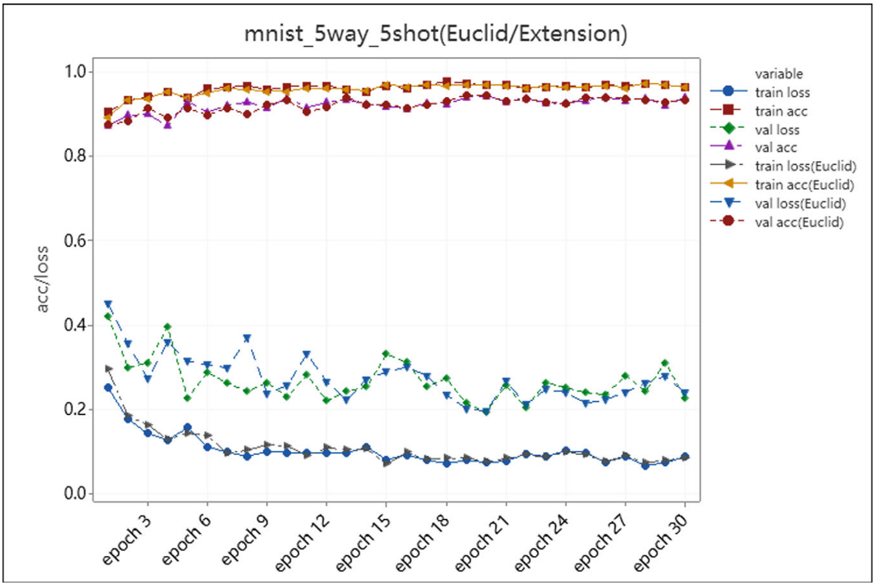

Fig. 1.4 Comparison two distance ways for prototypical network with the same 5-way 5-shot

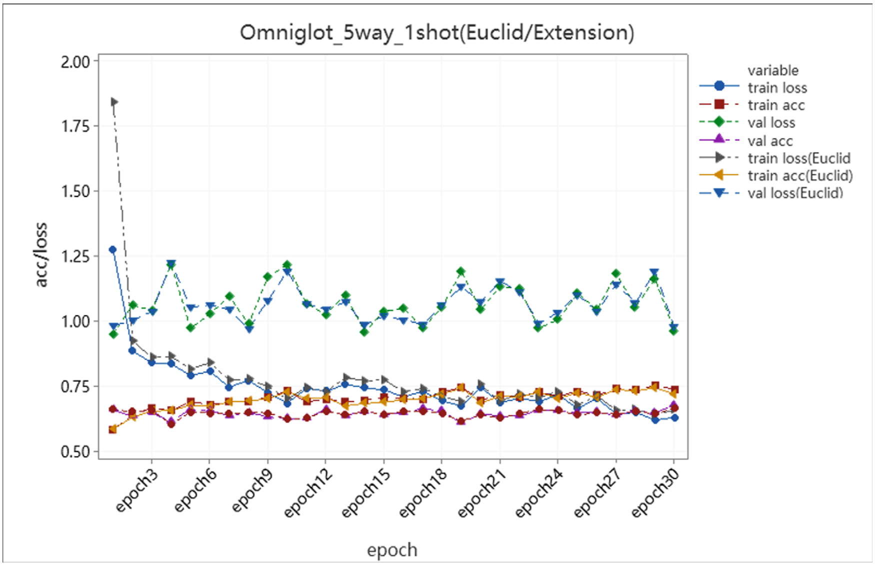

Fig. 1.5 Comparison of two distance ways for the prototypical network with the same Omniglot dataset 5-way 1-shot

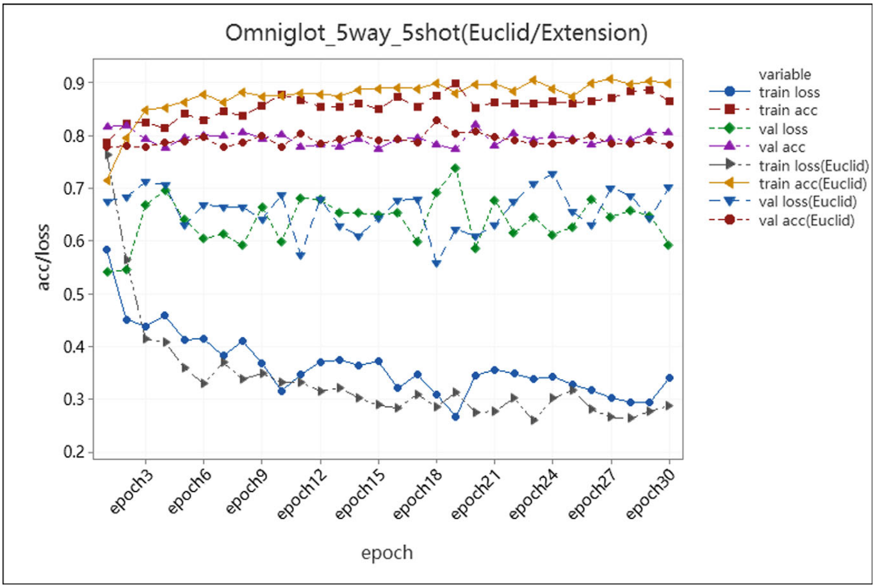

Fig. 1.6 Comparison two distance ways for the prototypical network with the same 5-way 5-shot

Table 1.3 Based on two different metric distances of few-shot classification accuracies on Omniglot; We all take the cluster number as k = 50, partition number is p = 10

Model	Dist	5-way Acc		20-way
		1-shot	5-shot	1-shot
Prototypical network	Extension	64.77%(↑0.07)	79.32%(↑0.33)	41.99%(↑0.25)
Prototypical network	Euclidean	64.71%	78.99%	41.74%

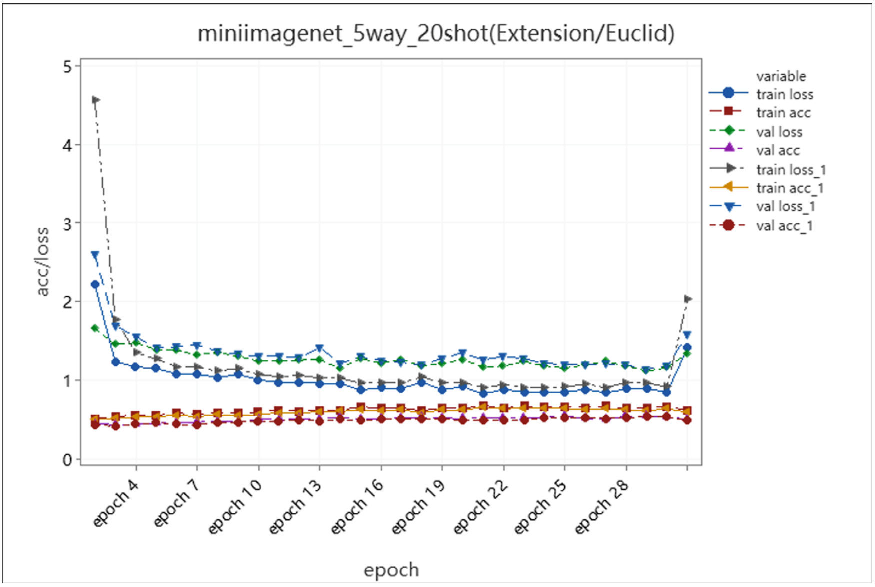

Fig. 1.7 Comparison of two distance ways for prototypical network with the same 5-way 20-shot

1.5 Discussion

The prototypical network is a meta-learning method based on metric space14. It is helpful to improve generalization ability by improving the query point's search for prototypes in embedding space. Compared with the prototype network with label learning, the data set without label learning is more difficult, in which the automatic clustering tasks construction method in unsupervised meta-learning (CACTUS) is adopted. Our main work is to further study the measurement method between the query point and the prototype in the embedded space, to improve the generalization ability of experiments in the query set15. And we demonstrate that based on Extension distance meta-learning we can achieve better performance in learning downstream tasks. At the same time, it can be seen from the experiment that the task construction mechanism is also very important. The paper mainly adopts the K-means algorithm for clustering division16. The definition of distance in extensions is

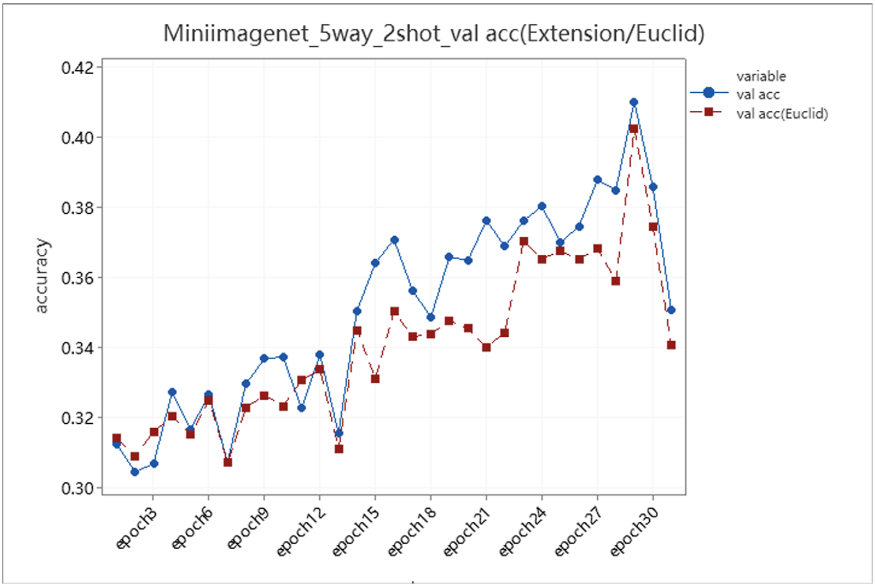

Fig. 1.8 Comparison of two distance ways for prototypical network with the same 5-way 2-shot

Table 1.4 Based on two different metric distances of few-shot classification accuracies on Miniimagenet, we take the cluster number as k = 50, the partition number as p = 10 for 5-way, 20-shot; And we take the cluster number as k = 100, the partition number is p = 50 for 5-way, 5-shot

Model (Miniimagenet)	Dist	5-way Acc	
		20-shot	5-shot
Prototypical network	Extension	50.37%(↑1.45)	41.62%(↑1.25)
Prototypical network	Euclidean	48.92%	40.37%

Table 1.5 Based on two different metric distances of few-shot classification accuracies on Miniimagenet. We take the cluster number as k = 500, the partition number is p = 100 for 5-way, 2-shot

Model (Miniimagenet)	Dist	Train loss	Val loss	Train acc	Val acc
Prototypical network	Extension (5way-2-shot)	2.35	2.54	57.17%(↑2.36)	35.06%(↑1.0)
Prototypical network	Euclidean (5way-2shot)	3.94	3.69	54.81%	34.06%

also called extension distance, which is a new distance measure proposed to make up for the inability to describe the process of qualitative change in classical mathematics. Quantitative change and qualitative change can be visually defined. Understanding the lateral distance is also very meaningful in extensions, side distance can further describe the distribution of the optimal value, also reflected in some papers 17. K-nearest neighbor and K-means clustering algorithm also can learn from the side distance, and extension from the side distance can also find out the initial clustering centers, and optimize the clustering center, introducing the idea of extension distance [18–20].

1.6 Conclusion

This paper introduces a novel distance measurement to evaluate the distance between the prototype and query point in embedding space. The relationship between a point and an interval in extensions can be explained with Extension distance. Introducing the extension from the concept, and designing a new extension distance at the same time, the experimental results show that our method unlike the Euclidean distance is better to measure query point and prototype, which also makes the classification more effective. And in the next work, we can go further explore metric distance meta-learning and extensions based on many kinds of literature, which can study the combination and application of more theoretical knowledge.

Author Contributions J. J., Z was mainly responsible for data collection, code convenience, and paper writing as the core contributor of this paper. W. F., W led the project and conceive the main idea of this research and L. M. P improved the quality of the whole paper.

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Data Availability All the data utilized to support the theory and models of the present study are available from the corresponding authors upon request.

Conflicts of Interest The authors declare that there are no conflicts of interest regarding the publication of this article.

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Chapter 2
Low Carbon Scheduling of Thermal Power Unit Thermal Storage Capacity Based on Particle Swarm Optimization

Wenbin Cao, Mingkai Wang, Bo Han, Qi Chai, Hongtao Li, and Ying Liu

Abstract A novel low carbon scheduling method for thermal power unit storage capacity is introduced to address the limitations of traditional approaches. By employing a particle swarm optimization algorithm, this method optimizes the scheduling of thermal storage capacity while considering the operational characteristics of the thermal power units. Through an analysis of the unit's pressure parameters, capacity level, and fuel type, different carbon emission allowances are allocated to each unit based on a baseline. The operation mechanism of the heat storage device is then optimized. The proposed low carbon scheduling model is effectively solved using the particle swarm optimization algorithm. Experimental analysis demonstrates the favorable scheduling performance of this method for thermal power units, highlighting its potential for reducing carbon emissions and achieving efficient operations.

2.1 Introduction

As thermal power units will still occupy the main position in China's power supply structure for a long time, some scholars have studied how to transform existing thermal power units into carbon capture systems and convert them into carbon capture units to reduce carbon emissions and alleviate social and environmental pressures [1, 2]. Compared with traditional thermal power generation units, carbon capture units have more convenient and flexible regulation capabilities. By quickly adjusting the net power generation, the units can track the random fluctuations of wind power.

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Regarding carbon capture technology, existing literature has discussed the ability of carbon capture power plants to promote wind power consumption. However, the above research is limited to solar heat or carbon capture with fluctuating power output, and few people have explored the optimal scheduling of the three joint operations. With the further deepening of power reform, it is a trend to consider the carbon emission reduction of emerging renewable energy power plants and traditional thermal power units. Reference [3] studied the impact of carbon emissions trading and green technology investment under the carbon ceiling on manufacturing enterprises' low-carbon manufacturing decisions from the perspective of micro low-carbon economy. Reference [4] introduced an adaptive image swarm optimization algorithm called SA-EHO, which aimed to achieve the desired scheduling model of a microgrid (MG) incorporating electric vehicles and renewable energy sources (RES). However, the aforementioned methods primarily focused on scheduling and did not yield satisfactory low-carbon effects. Thus, to ensure the safe operation of the power grid, there is an urgent need to investigate a low-carbon scheduling approach for the thermal power unit's thermal storage capacity, considering carbon emission rights comprehensively. This study examines the operational characteristics of thermal power units in the context of carbon emission rights and establishes the operating mechanism of thermal storage devices based on this analysis framework. Leveraging the particle swarm optimization algorithm, we construct the objective function and scheduling model for low-carbon scheduling of the thermal power unit's thermal storage capacity, thereby achieving effective low-carbon scheduling in this domain.

2.2 Analysis of the Operating Characteristics of Thermal Power Units Considering Carbon Emission Rights

This paper utilizes the industry benchmark approach to determine the initial allowances, employing the carbon emission trading regulations currently being tested in China. The allocation of carbon emission allowances to various units is based on 11 baseline categories, which are determined by pressure parameters, capacity levels, and fuel types of the primary generating units. The calculation of these allowances is conducted using the equation outlined.

$$E_{i,t} = \delta_i P_t \tag{2.1}$$

Where, $E_{i,t}$ represents the carbon trading allowance of thermal unit i in time period t, δ_i represents the initial carbon emission allowance per unit of electricity of unit i, and P_t represents the output of thermal unit. The carbon dioxide emission of thermal power unit is related to the unit output, and the relevant expression is shown in (2.2).

$$E_{i,t}^C = \delta_i^C P_t \tag{2.2}$$

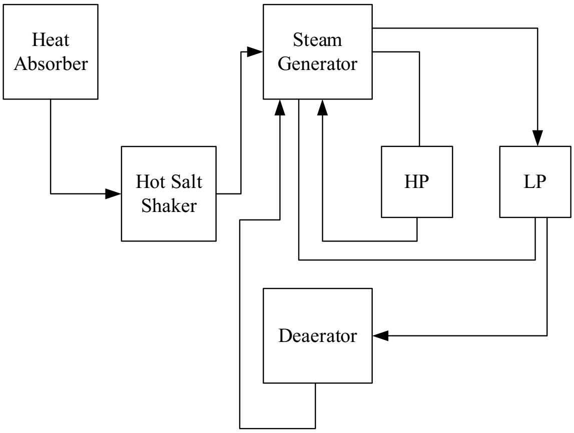

Fig. 2.1 Structure diagram of thermal power unit generating station

Where: $E_{i,t}^{C}$ is the actual system carbon emission of thermal power unit i at time t, and δ_i^C is the actual carbon emission intensity of unit i. Thus, the carbon trading cost of unit i can be calculated by (2.3).

$$C_{i,t}^{C} = C^{CO_2}(E_{i,t}^{C} - E_{i,t}) \tag{2.3}$$

Where: $C_{i,t}^{C}$ is the carbon trading cost of thermal unit i at time t, and C^{CO_2} is the carbon trading price factor.

Taking the most widely used thermal power plant with thermal storage as an example, we introduce the basic structure of thermal power generation [5–7], as shown in the (Fig. 2.1).

The working principle of thermal power plant is as follows: the fixed sun mirror in the concentrating collector system can track the solar radiation in real time and converge the light energy to the collector at the top of the tower. The collector temperature rises and thus heats the heat-conducting fluid, which, in the process of flowing, transfers heat to the power generation unit to produce steam to drive the turbine to generate electricity; at the same time, the redundant heat flows into the heat storage system through the heat-conducting fluid, and the heat between the hot and cold salt tanks is exchanged to realize the change of heat storage and discharge. This satisfies the time-sharing utilization of heat and plays the role of output leveling, which makes the solar thermal power plant excellent scheduling capability. The energy flow process of the thermal power plant is shown in the (Fig. 2.2).

The above diagram clearly shows the energy conversion during the operation of thermal power generation, which shows that thermal power generation realizes the step-by-step conversion of light-thermal energy to electrical energy, and there is storage and release of redundant heat. This unique operating characteristic makes thermal power generation different from other new energy generation [8], which can realize smooth and controllable power output and is conducive to grid dispatching and regulation, which is of positive significance to improving grid peaking pressure.

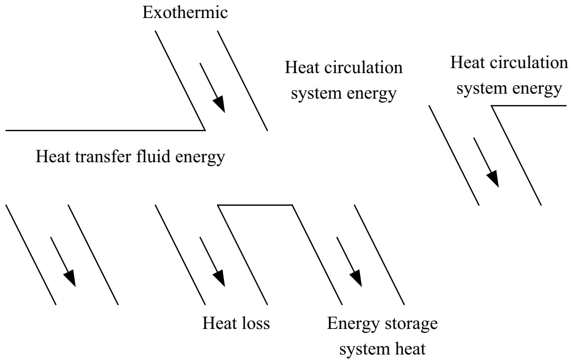

Fig. 2.2 Energy flow process of thermal power unit

The expression of light-to-heat power conversion in the concentrated heat collection system is as follows:

$$P_t^{SF} = \eta_{sh} S_{SF} D_t \tag{2.4}$$

Where, P_t^{SF} represents the thermal power obtained by the heat absorber in time t, η_{sh} represents the solar thermal conversion efficiency, S_{SF} represents the area occupied by the generator set, and D_t represents the direct irradiation index in time t. The thermal energy collected by the heat absorber can either be stored by the thermal conductivity fluid to the thermal storage device or directly supplied to the power generation system for power generation at peak load, while the absorbed thermal energy in the heat absorber can be discarded to ensure the smooth operation of the solar thermal power plant.

$$P_t^{SF} = (P_t^{esp,h} + P_t^{TS,c} - \eta_{dis})\Delta t \tag{2.5}$$

Where, $P_t^{esp,h}$ represents the thermal power of the heat absorber directly used for power generation in section t, $P_t^{TS,c}$ represents the thermal power of the thermal storage device in time t [9, 10], and η_{dis} represents the exothermic efficiency of the thermal storage system. Limited to the material characteristics of the energy storage device itself, heat dissipation cannot be avoided, and the calculation formula is as follows:

$$C_t^{TS,h} = (1 - \eta_{loss}) C_{t-1}^{TS,h} \Delta t \eta_{cha} \tag{2.6}$$

Where, $C_t^{TS,h}$ represents the heat storage state of the heat storage device at time t, η_{loss} represents the heat dissipation coefficient, η_{cha} represents the heat storage efficiency of the heat storage system, and Δt represents the time interval.

The equivalent output power of thermal power plant is jointly determined by the power generated by the thermal energy of both the heat collection device and the heat storage device, and the calculation formula is shown.