Task-Significance-Aware Meta Learning for Few-Image-Based Structural Damage Recognition

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ABSTRACT

Recently, structural damage recognition has gained significant progress using deep learning and computer vision techniques. However, massive training images, the interclass balance and completeness of damage categories are essential to ensure recognition accuracy. In addition, the generalization ability for new damage categories and robustness under real-world scenarios are limited. This study proposes a task-aware meta-learning paradigm using limited images for universal structural damage segmentation. First, a novel task generation strategy instead of random sampling is designed based on feature density clustering. A synthetical metric of Jaccard distance and Euclidean distance is established to measure the feature similarity among multitype damage images. The class separability discovered in the high-level feature space of multi-type structural damage enhances the interpretability of randomly-generated tasks for conventional meta-learning. Second, a dual-stage optimization framework is built based on Model-Agnostic Meta-Learning (MAML), comprising an internal optimization stage of the semantic segmentation model (U-Net) and an external optimization stage of the meta-learning machine. Third, a set of core samples around the cluster center is selected to form an additional query pool and evaluate the tasksignificance scores of different tasks within a meta-batch by the same criteria. The task-significance scores are utilized in the external optimization to control the orientation of gradient updates towards more significant tasks. To verify the effectiveness and necessity of the proposed method, ablation experiments are performed using a multi-type structural damage dataset, including concrete crack, steel fatigue crack, and concrete spalling. The proposed method outperforms directly training the original U-Net and the conventional MAML algorithm using only a handful of training samples with improvements in segmentation accuracy. In addition, the improvement in recognition accuracy increases when using fewer training images, further indicating the efficacy of the proposed method. The generalization ability for new structural damage of steel corrosion is also demonstrated.

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INTRODUCTION

During the service period for decades, civil infrastructure is inevitably affected by various complex factors (including environmental erosion, material aging, fatigue load, and disaster events such as typhoons, earthquakes, and other emergencies), leading to the irreversible appearance and accumulation of structural damage. There will be many different damage types, such as concrete cracks, steel fatigue cracks, concrete spalling, cable corrosion, etc. Timely identification of the location, morphology and geometrical characteristic of surface damage to ensure the resistance and service performance of structures is a crucial problem to be urgently solved in engineering practice.

In recent years, with the development of artificial intelligence and the collectible large-scale datasets, deep learning has shown prominent potential in multiple visual disciplines, especially for vision-based structural damage detection [1-5]. In deep learning-based methods, convolutional neural networks (CNN) are utilized to extract the multi-level features of input images to map the damage annotations [6-9]. Bao and Li proposed a machine learning-based paradigm of structural health diagnosis using mathematical algorithms to process various monitoring data and predict the structural performance and state in high-dimensional feature space [10]. Model-Agnostic Meta-Learning (MAML) was proposed based on the initial parameter optimization, regarded as the most representative meta-learning algorithm. Recently, meta-learning has also been applied to structural health monitoring and damage detection, and an attribute-based few-shot meta-learning paradigm has been established for structural damage classification [11,12].

Currently, most supervised learning approaches require sufficient image quantity and feature abundance to ensure recognition accuracy and robustness in various scenarios, leading to parameter redundancy inevitably in specific tasks. In general, the CNN-based methods are mainly performed on a particular dataset, lack the generalization to new onsite images, and the accuracy is limited to the number of training samples, the equilibrium, and the completeness of different categories. In the case of limited supervision, forming an assessment model for universal structural damage identification is challenging. To address the above challenge, inspired by the MAML algorithm, this study proposes a meta-learning-based algorithm for multi-type structural damage segmentation on small-scale datasets. Unlike the other few-shot learning approaches, it only utilizes a few samples to train a basic meta-learning model applicable to multiple datasets.

METHODOLOGY

Method Overview

The existing few-shot segmentation methods usually rely on a large-scale dataset to train the basic model migrating to the unseen tasks to obtain acceptable accuracy. In contrast to prior work, aiming at the condition of limited supervision under actual scenarios, a task generation strategy is proposed based on the partition of feature distribution space, and a task-significance-aware dual-stage optimization paradigm is established inspired by the MAML algorithm to extract underlying features of multi-type structural damage.

The overall schematic of the proposed method is shown in Figure 1. In the semantic segmentation problem, the artificially defined categories only based on the surface information of the images cannot precisely interpret the deep semantic features of images. For the issue of interpretability in random task generation, the proposed method designs a density clustering-based task generator for obtaining the task sampling boundaries and core samples in feature space. In addition, the task-significance-aware algorithm is applied over the dual-stage optimization paradigm to train the meta-learning machine adapted to massive episode test tasks. Meanwhile, the significance coefficient is introduced to constrain the external optimized direction, which is evaluated by the data of the query pool contained in cluster core samples.

Task Generation Algorithm

The task generation algorithm is proposed to address the problem of interpretability of randomly-generated tasks and ambiguity of semantic categories of identification for multi-type structural damage. As shown in Figure 1, the task generator includes three components: feature extractor, feature clustering, and task sampling.

The feature extractor is a deep convolutional network for obtaining the underlying features of all images in D_{train}. In order to acquire more reliable feature vectors, the encoder module of the current initial model f_{θ^n} is utilized as the feature extractor and updated along with the training process. According to the difference of semantic information that the model pays attention to in different training stages, the extractor can be adaptively optimized to get the variational feature representation after each parameter iteration. After all the training data pass through the feature extractor, a global average pooling operation is employed to integrate the global spatial information of the feature map, which is converted into high-dimensional feature vectors.

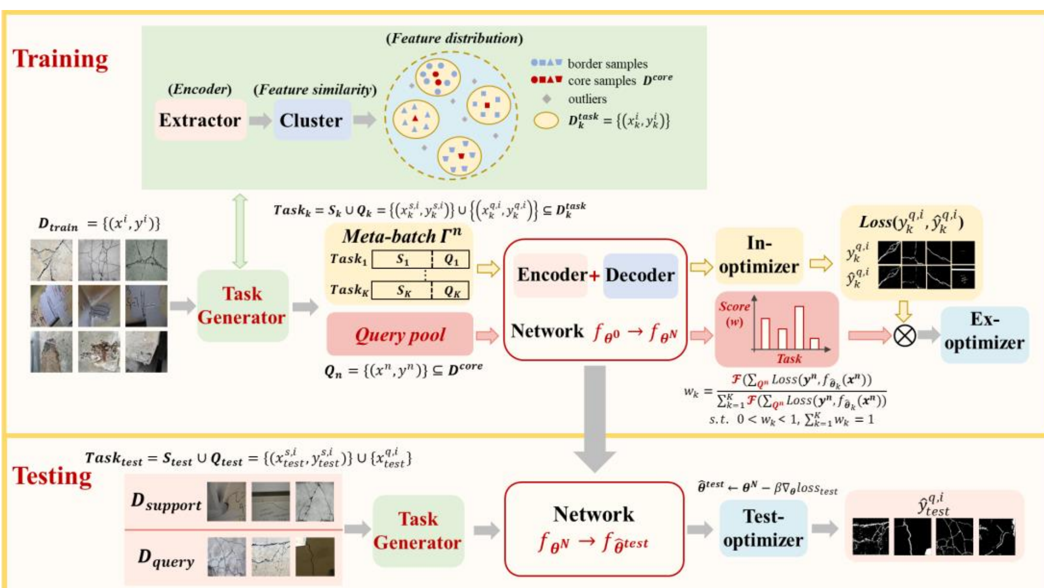

Figure 1. Flowchart of task-significance-aware meta-learning method

Based on class separability in the high-level feature space of multi-type structural damage, the clustering method is adopted to partition feature points and generate tasks. And in the feature space, the smaller the sample distance, the more learnable features are between them. Therefore, the obtained clusters can be taken as the task sampling boundaries, and an individual task is sampled from a specific class cluster. To cluster samples, the first is to select an appropriate metric to measure the similarity between data points. Since a meta-batch contains multiple tasks, the feature distribution must exist in relatively complete partitions. The metric space should maximize the inter-class distance and minimize the intra-class distance. In such a situation, the conventional Euclidean or cosine distance is difficult to perform well in high-dimensional space; thus, feature diversity vanishing is caused by dimension superposition. Inspired by the re-ranking of image retrieval, the proposed model adopts the comprehensive similarity based on Euclidean distance and k-nearest Jaccard distance as the clustering index. The optimized k-nearest Jaccard similarity J_{ij} can be written as

$$J_{ij} = \frac{\sum_{n=1}^{N} \min[(k_i^n \times E_{in}),(k_j^n \times E_{jn})]}{\sum_{n=1}^{N} \max[(k_i^n \times E_{in}),(k_j^n \times E_{jn})]}, E_{ij} = \sqrt{\sum_{c=1}^{C} (\frac{v_c^i - v_c^j}{S_c})^2}, S_c = \sqrt{\sum_{n=1}^{N} (\frac{v_c^n - \overline{v_c}}{N})^2}, \ \overline{v_c} = \sum_{n=1}^{N} \frac{v_c^n}{N} \qquad (1)$$

where S_c and $\overline{x_c}$ represent the variance and average of the *c*-dimension of the entire output feature vectors, respectively. For data x^i, transform the *k*-nearest set into 0-1 vector $k^i = (k_i^1, k_i^2, ..., k_i^n, ..., k_i^N)$, if $x^n \in R^i$, $k_i^n = 1$, otherwise, $k_i^n = 0$.

As a more reliable and mathematical measure of sample feature similarity, the comprehensive similarity integrates the relationship and feature distribution of samples, avoiding the vanishing of feature diversity. Based on above feature metric, to further generate the sampling boundaries of each task, a clustering method called density-based spatial clustering algorithm (DBSCAN) is adopted to achieve partitioning data points in high-dimensional feature space. It regards a class cluster as a high-density region separated by low-density regions, and a class cluster consists of a set of core samples and border samples. The core points locate in the high-density areas as the cluster center with sufficient border points in the surrounding. Data points that do not belong to any cluster in the low-density regions are called outliers.

Task-Significance-Aware Dual-stage Optimization Paradigm

Overall, the proposed algorithm adopted internal-external dual-stage optimization mechanism to train the meta-learning machine. On small-scale training dataset, the difference of image features among various episodic tasks leads to the problems of instability and insufficient robustness during the training process. Considering effectiveness of different tasks on the new test task, the proposed meta-learning method introduces task-significance-aware module to constrain the orientation of external optimization, which evaluates the significance scores of different tasks within a meta-batch by means of a standard query pool consisting of the core samples in clusters.

For the internal optimization, a group of updated parameters can be calculated in the internal optimizer with the internal loss using the support images in each task. The learning rate α can be fixed as a hyperparameter. The model is optimized for the performance of parameters to the support images, so that the internal meta-objective is:

$$\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}} \leftarrow \boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}} - \alpha \nabla_{\theta} loss_{in}, \boldsymbol{F}_{\theta^n} = \arg\min_{\theta} \frac{1}{S} \sum_{i=1}^{S} Loss(y_k^{s,i}, f_{\theta_k^n}(x_k^{s,i})) \tag{2}$$

where $\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}}$ represents the parameters being updated on the *k*th task of the *n*th meta-batch with the initial value $\boldsymbol{\theta}^{\boldsymbol{n-1}}$.

For the external optimization, the query images of each task are regard as the input of the updated network to calculate the loss. In view of the contribution and effect of each task in current meta-batch, the weighted sum of the query loss is computed as the external optimization loss $loss_{ex}$. In the external optimizer, $loss_{ex}$ is used to accomplish meta-optimization across tasks with the updating of initial parameters via gradient descent algorithm. For the updating of initial parameters of the network based on the meta-batch, the task-significance-aware optimization function can be defined as:

$$\boldsymbol{\theta}^{\boldsymbol{n}} \leftarrow \boldsymbol{\theta}^{\boldsymbol{n-1}} - \beta \nabla_{\theta} loss_{ex}, \boldsymbol{F}_{\theta^n} = \arg\min_{\theta} \sum_{k=1}^{K} w_k \frac{1}{Q} \sum_{i=1}^{Q} Loss(y_k^{q,i}, f_{\theta_n^k}(x_k^{q,i})) \tag{3}$$

where β denotes the external learning rate, $\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}}$ represents the parameters updated on the *k*th task of the *n*th meta-batch, w_k is the task-significance coefficient following the fundamental principle of $0 < w_k < 1$, $\sum_{k=1}^{K} w_k = 1$. The larger value of w_k, the greater control effect of the task to the meta-learning machine optimization. The task-significance coefficient can be calculated as:

$$w_k = F\{\sum_{Q^n} Loss[y_i^n, f_{\theta_k}(x_i^n)]\} \Big/ \sum_{k=1}^{K} F\{\sum_{Q^n} Loss[y_i^n, f_{\theta_k}(x_i^n)]\} \tag{4}$$

where $Q^n = \{(x_i^n, y_i^n)\}_{i=1}^{N_{Q^n}}$ represents the meta-batch query pool, and F denotes the task-significance-aware function as a subtraction function adjusting the amplification effect of task query errors. Diverse forms of task-significance-aware function can be chosen to fulfill the task-aware requirement under different datasets. The details of task-significance-aware dual-stage optimization paradigm is outlined in Algorithm 1.

Algorithm 1. Task-Significance-Aware Meta-learning method

Input: multi-type structural damage dataset $D^{train} = \{(x_i^{train}, y_i^{train})\}$; learning rate α, β; the number of Meta-batch N

Output: trained initial parameters $\boldsymbol{\theta}^{\boldsymbol{N}}$

1: randomly initialize θ^0
2: repeat $n = n + 1$ from $n = 0$
3: extract feature vector of x_i^{train}, Calculate the similarity matrix $\boldsymbol{J} \in \mathbb{R}^{N_{train} \times N_{train}}$
4: Sample meta-batch tasks $\boldsymbol{\Gamma}^{\boldsymbol{n+1}}$ and query pool Q^n by means of DBSCAN
5: for all $T_k \subseteq \boldsymbol{\Gamma}^{\boldsymbol{n+1}}$ do
6: optimize parameters $\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}}$ based on S_k: $\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}} \leftarrow \boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}} - \alpha \nabla_{\theta} loss_{in}$
7: compute $Loss_{Q_k}$ and $Loss_{Q^n}$ utilizing $\boldsymbol{\theta}_{\boldsymbol{k}}^{\boldsymbol{n}}$
8: compute w_k and $Loss_{ex} = \sum_{k=1}^{K} w_k Loss_{Q_k}$
9: update $\boldsymbol{\theta}^{\boldsymbol{n}}$: $\boldsymbol{\theta}^{\boldsymbol{n+1}} \leftarrow \boldsymbol{\theta}^{\boldsymbol{n}} - \beta \nabla_{\theta} loss_{ex}$
10: until $n = N$

RESULTS AND DISCUSSION

The collected images are roughly divided into slight structural damage (concrete crack and steel fatigue crack) and regional structural damage (concrete spall and steel corrosion) and captured from multiple actual scenes with a resolution of 512 × 512. Figure 2 shows representative annotated images for multi-type structural damage.

For slight structural damage, the Dice Loss is utilized for optimization to eliminate the imbalance of foreground and background. For regional damage with fair proportion, the Cross-Entropy Loss is selected, and the calculations are expressed respectively as

$$L_{Dice}=\frac{1}{n}\sum_{j=1}^{n}\frac{1-2\sum_{i=1}^{H\times W}p_i\times y_i}{\sum_{i=1}^{H\times W}p_i+y_i},L_{ce}=-\frac{1}{n}\sum_{i=1}^{H\times W}y_i\log(p_i)+(1-y_i)\log(1-p_i) \tag{5}$$

where H and W represent the height and width of the input images, respectively. The p_i denotes the probability that the ith pixel is predicted to be a positive sample, and y_i denotes the ground-truth label for the ith pixel.

In order to reinforce the constraint of the meta-batch query pool in the external optimizer, pixel-Dice Loss is used to calculate the query pool error as

$$Loss_{Q^n}=\sum_{i=1}^{H\times W}[1-2p_iy_i/(p_i+y_i)] \tag{6}$$

The mIoU (mean intersection-over-union) and mPA (mean pixel accuracy), as widely used metrics, are chosen to measure the segmentation performance as

$$\text{mIoU}=\frac{1}{C}\sum_{i=1}^{C}\frac{p_{ii}}{\sum_{j\neq i}p_{ij}+\sum_{j\neq i}p_{ji}+p_{ii}},\text{mPA}=\frac{1}{C}\sum_{i=1}^{C}\frac{p_{ii}}{\sum_{j\neq i}p_{ij}} \tag{7}$$

where C denotes the total number of pixel categories, and P_{ij} denotes the number of pixels in the ith class classified to the jth class.

For single-type damage identification, a total of 80 images with a resolution of 512×512 in the query set are predicted to generate binary damage maps. Some representative semantic segmentation results of different types of structural damage in the query set are shown in Figure 3. The results illustrate that the task-significance-aware meta-learning method achieves the optimal recognition performance for various damage types with multi-morphology, diverse severities, and multiple background complexities. Compared with the original U-Net and MAML, the proposed method can identify more explicit damage margins, and the anti-interference for complex background noise and damage-like structural boundaries has improved significantly.

Figure 2. Representative images with pixel annotation

To validate the generalization ability to new types of damage of proposed method, the primary dataset collects concrete crack, steel fatigue crack, and concrete spalling images to train the meta-learning machine for the steel corrosion category, including 80 query images without annotations and 40 labeled support images. Figure 4 shows partial comparative segmentation results of steel corrosion images, and Figure 5 shows the boxplots of evaluation metrics. By contrast, the average mIoU and average mPA of the proposed method increased by 5.1% and 0.6% with better robustness and generalization.

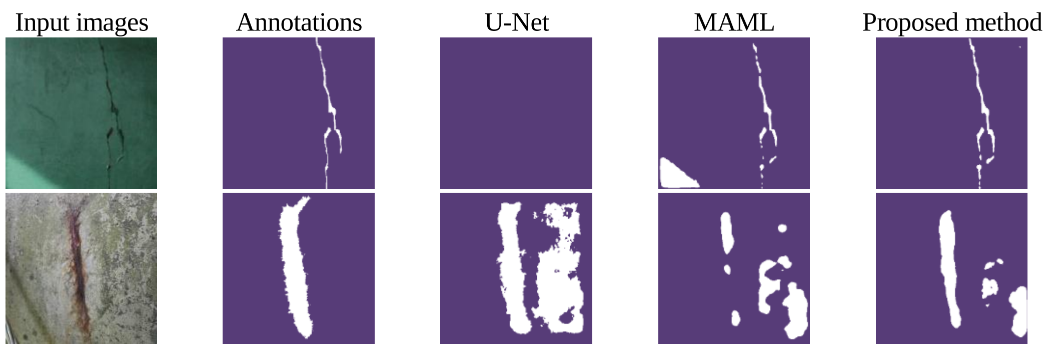

Figure 3. Segmentation results of different damage types in the query set

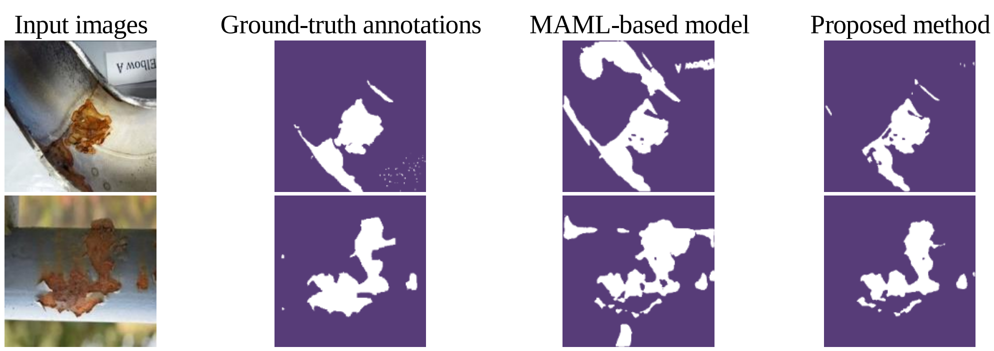

Figure 4. Some representative segmentation results of steel corrosion

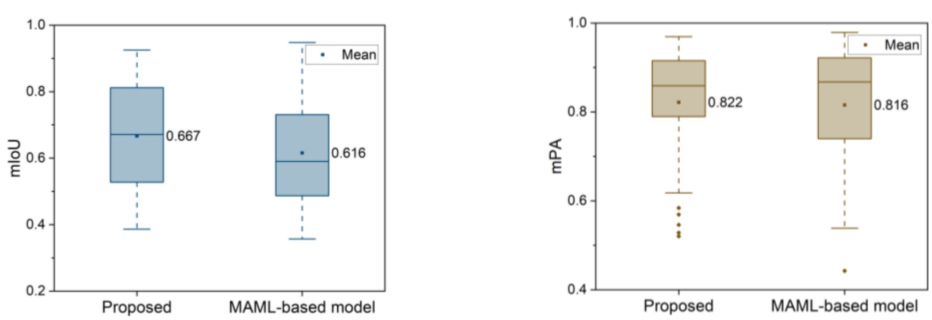

Figure 5. Comparative boxplots of evaluation metrics for steel corrosion

CONCLUSIONS

This study introduces a task-significance-aware meta-leaning method for multi-type structural damage detection under limited supervision. The proposed meta-learning model learns cross-task knowledge and improves segmentation accuracy in two ways. A task generation strategy is designed based on feature density clustering to solve the poor interpretability of randomly generated tasks. A novel similarity metric of Jaccard distance and Euclidean distance is introduced to address the vanishing of separability in feature space. The task-significance-aware dual-stage optimization paradigm is established to learn the shared potential information among different categories. As the standard samples around the cluster center, the meta-batch query pool is formed to evaluate the significant score of different tasks guiding the orientation of external optimization. Experimental results illustrate the effectiveness of the proposed method.

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