

Multiple-environment Self-adaptive Network for Aerial-view Geo-localization

Tingyu Wang^a, Zhedong Zheng^b, Yaoqi Sun^{a,c}, Chenggang Yan^{a,*}, Yi Yang^d,
Tat-Seng Chua^e

^a*Intelligent Information Processing Lab, Hangzhou Dianzi University, China*

^b*Faculty of Science and Technology, University of Macau, China*

^c*Lishui Institute of Hangzhou Dianzi University, China*

^d*College of Computer Science and Technology, Zhejiang University, China*

^e*Sea-NErT Joint Lab, School of Computing, National University of Singapore, Singapore*

Abstract

Aerial-view geo-localization tends to determine an unknown position through matching the drone-view image with the geo-tagged satellite-view image. This task is mostly regarded as an image retrieval problem. The key underpinning this task is to design a series of deep neural networks to learn discriminative image descriptors. However, existing methods meet large performance drops under realistic weather, such as rain and fog, since they do not take the domain shift between the training data and multiple test environments into consideration. To minor this domain gap, we propose a Multiple-environment Self-adaptive Network (MuSe-Net) to dynamically adjust the domain shift caused by environmental changing. In particular, MuSe-Net employs a two-branch neural network containing one multiple-environment style extraction network and one self-adaptive feature extraction network. As the name implies, the multiple-environment style extraction network is to extract the environment-related style information, while the self-adaptive feature extraction network utilizes an adaptive modulation module to dynamically minimize the environment-related style gap. Extensive experiments on three widely-used benchmarks, *i.e.*,

*Corresponding author

Email addresses: wongtyu@hdu.edu.cn (Tingyu Wang), zhedongzheng@um.edu.mo (Zhedong Zheng), syq@hdu.edu.cn (Yaoqi Sun), cgyan@hdu.edu.cn (Chenggang Yan), yangyics@zju.edu.cn (Yi Yang), chuats@comp.nus.edu.sg (Tat-Seng Chua)

University-1652, SUES-200 and CVUSA, demonstrate that the proposed MuSe-Net achieves a competitive result for geo-localization in multiple environments. Furthermore, we observe that the proposed method also shows great potential to the unseen extreme weather, such as mixing the fog, rain and snow.

Keywords: Cross-view Geo-localization, Deep Learning, Image Retrieval, Multi-source Domain Generalization, Multi-platform Collaboration

1. Introduction

Aerial-view geo-localization generally refers to retrieving the corresponding images between drone and satellite platforms. It recently could be deployed to many fields, such as drone navigation, event detection, aerial photography, and
5 so on [1, 2, 3]. In application, given a drone-view image as the query, the retrieval system intends to search the most relevant satellite image from the candidate gallery. The satellite-view images possess geo-tag information, such as GPS. Thus the drone can naturally determine its geographic location. Compared with ground-view images with more occlusion, *e.g.*, tree, drone-view images support
10 excellent visibility. However, aerial-view geo-localization remains challenging due to the cross-view domain shift caused by the viewpoint and the environment.

Convolutional neural networks (CNNs) have recently received primary support in aerial-view geo-localization due to the strong potential to learn invariant image representations. Relying on CNNs, a two-branch network [4, 5] as the
15 prototype has been widely employed in related studies. The metric learning [6, 7] and the classification loss [1, 2] are two predominant choices to optimize this prototype. A number of extension works adjust the spatial layout of image semantics [8] to extract view-invariant features or deploy part-based matching [2] to roughly align local information. All these existing methods concentrate on
20 mitigating the cross-view domain gap introduced by viewpoint change. One scientific problem raises: how can the model cope with the environmental domain shift? Recently, some researchers [9] point out that a trained network is

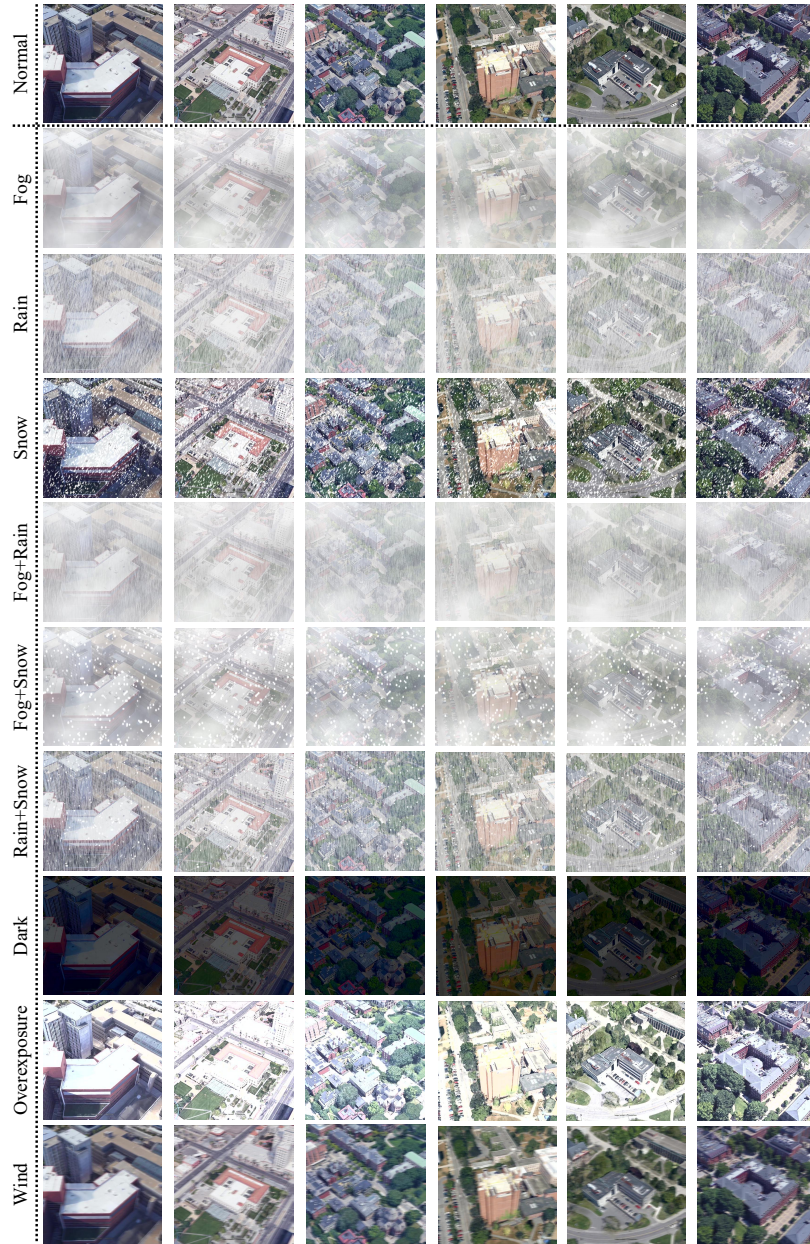


Figure 1: Examples of synthesized environments on University-1652 [1], which raise challenges on the robustness of the drone vision. Specifically, we generate these images by adding different environmental styles into the normal drone-view images. Each column and row corresponds to different geographical locations and environments.

easy to collapse for unfamiliar input distributions. As a result, existing networks are likely to fail in multi-environment inference of geo-localization. Our
25 research does not focus on improving the general matching accuracy. In contrast, we mainly study the robustness of current methods on cross-platform media against different environments. Specifically, we aim to relieve the negative impact of geo-localization in noisy environments, such as rain and fog. This robustness task is also non-trivial since the drone can easily encounter
30 environmental changes during flight. It is well known that bad weather can lead to invisibility of geographic targets and even cause serious flight accidents [10]. Therefore, employing the aerial-view geo-localization system to retrieve in multiple environments is a meaningful and practical topic. This topic touches on domain generalization (DG) [11], and a direct effort is to let the geo-localization
35 model 'remember' the distribution of a location in different environments during training. However, many studies [11, 12, 13] in domain generalization have demonstrated that forcing the entire model or features to be domain invariant is challenging. We know that humans recognize a previously seen location again by eliminating the interference caused by environmental changes rather than
40 remembering how the location looked under different environments. This human cognitive mechanism inspires our research. Specifically, when testing, we hope that the trained drone-to-satellite geo-localization system can adaptively filter out the domain shift caused by environmental changes. While achieving this goal is non-trivial, two issues need to be discussed. One is the reproduction of
45 the environmental style information. We consider a reasonable assumption that the seen environments can replay in a new scenario. Therefore, we need the system to be able to independently reproduce different environmental style information from the inputs during testing. Then the style information is utilized to balance the environmental domain shift. To do so, we expand the training
50 data for environmental diversity first. The data collection is expensive and difficult since one fixed position calls for images shot in different weather. Another reason is that unlike the acquisition of ground-level images, the collection of drone-view images needs to be operated by professionals. Generative adversar-

ial networks (GANs) [14] and data augmentation are two appealing choices to
55 replace manual dataset production. GANs recently can synthesize images that
are not only of high quality but also possess sufficient diversity. However, the key
of our research is not to generate stylized images with high quality. Considering
the speed and flexibility, we abandon GANs and choose an off-the-shelf image-
based style transformation library [15] to pre-process images. After processing
60 images, we obtain nine synthetic environmental images for one geographical lo-
cation, *i.e.*, fog, rain, snow, fog add rain, fog add snow, rain add snow, dark,
overexposure, and wind (see Figure 1). We then require the system to be able
to extract different environment knowledge to achieve reproduction. In vanilla
CNNs, the image information contained in extracted features is tangled. Some
65 methods [13, 12] suggest that representations can be disentangled into different
parts using specific domain labels or domain-related prior knowledge. We follow
this idea and encode the environmental information from input images by su-
pervised learning, where the environmental labels are automatically annotated
during the image transformation. Another issue is how to utilize the style infor-
70 mation to minimize the environmental style gap. We suppose that the identity
information is domain-agnostic and the environmental style is domain-specific
for one location. Some reference methods retain only the domain-agnostic in-
formation for downstream visual tasks [16, 11] or employ instance normaliza-
tion [17] to resist the effect of image style changes [18]. Unlike these methods,
75 our system aims to align the domain-specific distribution on the fly. To achieve
this goal, we first borrow experience from IBN-Net [18] to process images and
obtain visual features. IBN-Net integrates batch normalization (BN) [19] and
instance normalization (IN) into residual blocks of shallow layers. BN is used
to retain the discrimination of features [20, 21], and IN is employed to filter out
80 domain-specific style information from the content [18]. However, IN applies
the same treatment to multiple styles of content. To satisfy the dynamic adapt-
ability, we further introduce spatially-adaptive denormalization (SPADE) [22]
and integrate SPADE into a residual structure, called Residual SPADE, in our
system. Same as SPADE, Residual SPADE is a conditional normalization mod-

85 ule that allows flexible modulation of image styles by scales and biases learned
from the external data. In light of the above analysis, we propose a two-branch
learning framework called Multiple-environment Self-adaptive Network (MuSe-
Net). The design of MuSe-Net is based on IBN-Net yet with more scalability. In
particular, we insert Residual SPADE after the instance normalization layer of
90 IBN-Net as the self-adaptive feature extraction network to construct one branch
of MuSe-Net. The other branch of MuSe-Net is a multiple-environment style
extraction network, which parameterizes the environment information as inputs
of Residual SPADE. Two branches have the same inputs, ensuring that the
self-adaptive feature extraction network can utilize the corresponding environ-
95 mental information from the style extraction network to dynamically close the
environmental style gap.

The main contributions of this work are summarized as follows.

- We identify one key challenge, *i.e.*, the weather and illumination changes,
when applying the visual geo-localization system to the real-world sce-
100 nario. The large visual changes usually compromise the reliability of the
existing methods. To address this limitation, based on simulated multi-
weather data, we adopt an adaptive adjustment strategy of style infor-
mation and present an end-to-end learning framework called Multiple-
environment Self-adaptive Network (MuSe-Net). MuSe-Net applies a dual-
105 path CNN model to extract the environment-related style information and
dynamically minimize the environment-related style gap, such as weather
and light changes.
- To motivate the model to learn discriminative feature, we further introduce
a module called Residual SPADE, which utilizes the residual structure to
110 optimize the training of MuSe-Net.
- Extensive experiments on three prevailing multi-platform geo-localization
benchmark, *e.g.*, University-1652 [1], SUES-200 [23] and CVUSA [24],
show that our method achieves superior results for geo-localization in mul-

115 multiple environments. Meanwhile, for an unseen extreme weather, *i.e.*, mixing the fog, rain and snow, MuSe-Net still arrives at competitive results.

2. Related Work

In this section, we briefly discuss the relevant works in two aspects, including CNN-based cross-view geo-localization and domain generalization.

2.1. CNN-based Cross-view Geo-localization

120 Existing cross-view geo-location methods mostly focus on solving the visual gap caused by the changing appearance in different viewpoints. In order to gain the discriminative image representation, some pioneering works [25] make many efforts on hand-crafted feature matching. Due to the powerful capability on image representation [26], deep convolutional neural networks (CNNs) become the
125 prevalent choice for feature extraction. Follow this line, Workman *et al.* [27] first attempt to employ an AlexNet [28] pre-trained on Imagenet [26] and Places [29] to extract deep features for cross-view geo-localization. They prove that the top layers of CNN include rich information of geographic location. Further, Workman *et al.* [30] extend their work by minimizing the distance of cross-view
130 features and gaining improved performance. Lin *et al.* [31] define the matching task as similar to the face verification, and deploy the contrastive loss [32] to optimize a modified Siamese Network [33]. Later on, Hu *et al.* [7] insert a NetVLAD into the high-level layer of a Siamese-like architecture to aggregate the local feature, which facilitates image descriptors against the viewpoint
135 changes. Considering the importance of orientation, Liu *et al.* [4] encode the corresponding coordinate information into the network for the discriminative feature. Tian *et al.* [34] propose an orientation normalization network to alleviate the effect of the variation of orientation. Wang *et al.* [2] design a square-partition strategy to cope with the image rotation. Discussing on a limited
140 Field of View (FoV) setting, DSM [6] provides a dynamic similarity matching module to align the orientation of cross-view images. In order to align the

spatial layout information, Zhai *et al.* [24] encode and transfer the semantic information of ground images to aerial images. Regmi and Shah [35] apply a generative model to synthesize an aerial image from a panoramic image of the ground. Shi *et al.* [5] resort to the optimal transport theory to compare and adjust pairwise image distribution in the feature level. Another work of Shi *et al.* [8] directly utilize the polar transform to accomplish the pixel-level alignment of semantic information between ground images and satellite images. Lin *et al.* [3] exploit keypoints to enrich the model capability of learning robust features against viewpoints. Dai *et al.* [36] employ the heat distribution of the feature map to find and align critical regions in images from different viewpoints. In the aspect of optimizing different training objectives, Vo and Hays [37] investigate a variety of CNN architectures for cross-view matching and gain the best performance through employing a soft margin triplet loss to optimize a triplet CNN. Hu *et al.* [7] design a weighted soft-margin ranking loss that speeds up the convergence rate. Cai *et al.* [38] introduce a hard exemplar reweighting triplet loss to improve the retrieval. Zheng *et al.* [1] imitate the classification tasks and use instance loss [39] as the proxy targets to solve the cross-view image retrieval. Sun *et al.* [40] treat the multiview features as probability distributions and eliminate the feature differences by constraining the transmission loss. There are also some works [38, 8] that employ the attention mechanism to locate the interesting areas, which effectively promotes the discrimination of features.

In contrast to existing works, we study a new real-world scenario where the drone may encounter different weather and illumination, which leads to the same location with multiple domain distributions. For this multiple domain problem, we explicitly parameterize environmental information to align the domain distribution. Therefore, the drone is able to localize unseen positions in previously seen environments.

170 *2.2. Domain Generalization*

Generally, domain generalization (DG) is mentioned in multi-source domain problem. Similar to the topic of domain adaptation (DA), domain generalization tends to address the domain shift introduced by the statistical differences of multiple domains. However, compared with domain adaptation that employs
175 the labeled or unlabeled data of target domain during training, domain generalization concentrates on only leveraging the multi-source data to learn robust data representations which could be potentially useful in different marginal distributions, *e.g.*, unseen target domains.

There are many strategies that attempt to achieve domain generalization.
180 Some researchers argue that minimizing various well-designed distribution metrics [41, 42, 43] can realize multi-domain alignment. The statistical learning theory [44] suggests that the diversity of training samples can boost the generalization of learning models. Therefore, other researchers propose advanced augmentation algorithms [45, 46] to lessen the domain gap. Adversarial ap-
185 proaches [47] rely on confusing a domain discriminator to learn domain-invariant features, which can also alleviate the domain shift. Meta-learning [48] enables the model to learn new concepts and skills fast with a few training examples. Based on meta-learning, MAML [49] gains great success in domain generalization, and some improved MAML frameworks are also subsequently presented
190 in [50, 51]. Disentangled representation learning intends to learn the common and exclusive information from multiple domains and then processes these information separately to obtain robust features for future predictions. According to that, one group of approaches considers the disentanglement at the feature level. Khosla *et al.* [16] decompose a classifier based on the SVM into common vectors
195 and bias vectors, and abandon the bias part when applying in unseen domains. Later, Li *et al.* [11] employ the neural network to re-implement this concept. DMG [12] adopts a learnable mask to select and balance the domain-invariant and domain-specific features and demonstrates that analysing domain-specific components can assist to the prediction at test-time. Another solution supports
200 encoding the multiple knowledge into different latent spaces. Ilse *et al.* [13] pro-

vide a VAE [52]-type framework to learn three complementary sub-spaces for domain-invariant classification. There is also literature documenting the use of GANs [53] to construct two latent spaces: one for identity confirmation and the other serving the domain-related information.

205 3. Proposed Method

In this paper, we consider a more practical problem where the drone could encounter multiple environments, which cause the domain shift and drop the performance of aerial-view geo-localization. We challenge the problem by proposing a Multiple-environment Self-adaptive Network (MuSe-Net) (see Figure 2). In
 210 Section 3.1, we first provide the problem definition and notations. We then revisit the relevant technologies of our method in Section 3.2. Finally, we detail MuSe-Net in Section 3.3.

3.1. Problem Definition and Notations

The multiple environment aerial-view geo-localization task assumes the sce-
 215 nario that satellite-view images are constant while the style of drone-view images is variable with environmental changes. The different environmental information induces the existing methods which are difficult to search geographic target images with the same identities between different viewpoints. Our research focuses on reducing the interference of environmental styles when retrieving
 220 between two aerial viewpoints. Let $\mathcal{X} = \{x^i\}_{i=1}^N$, $\mathcal{Y}_{ID} = \{y_{ID}^i\}_{i=1}^N$ be the inputs and identity labels, respectively, for one multiple environmental aerial-view geo-localization dataset. N is the number of images, and $y_{ID} \in [1, C]$, and C indicates the number of identities. Conventional, the inputs \mathcal{X} consist of j domains, and $j \in \{1, 2\}$. \mathcal{X}_1 denotes the satellite-view domain and \mathcal{X}_2 denotes
 225 the drone-view domain. These two domains share the same identity labels \mathcal{Y}_{ID} . In our setting, we follow the previous definition and add one style space. In particular, holding \mathcal{Y}_{ID} constant, we expand the original drone-view domain \mathcal{X}_2 to multi-environment drone-view domain $\mathcal{X}_{2,k}$. The subscript $k \in [1, K]$,

and K indicates the number of environmental styles. Since the style of the
 230 satellite-view domain is constant, we denote this domain as \mathcal{X}_{1_k} and $k = 0$.
 Therefore, the added style label $\mathcal{Y}_{style} = \left\{ y_{style}^i \right\}_{i=1}^N$ includes $K + 1$ styles, *i.e.*,
 $y_{style} \in [0, K]$.

3.2. Relevant Technologies Revisit

IBN-Net [18]. Batch normalization (BN) maintains the discrimination of
 235 features by utilizing the global statistics (*i.e.*, mean and variance) recorded in
 training to normalize the testing sample. Instance normalization (IN) discards
 the global statistics. With the learned affine parameters, IN intends to close the
 style gap between each testing and training sample. Therefore, IN resists the
 effect of the style discrepancy but damages the discrimination simultaneously.
 240 Considering the advantages of BN and IN, IBN-Net integrates IN and BN as
 building blocks to extract style-invariable features and achieves a competitive
 result in the cross-domain scene parsing task.

Spatially-adaptive denormalization (SPADE) [22]. SPADE is a con-
 ditional normalization module that first requires external data to generate the
 learned affine parameters. Then the normalized activations are modulated by
 the learned affine parameters. SPADE can be simplified formulated as:

$$SPADE(u, v) = \sigma(v) \cdot \frac{u - \mu(u)}{\sigma(u)} + \mu(v), \quad (1)$$

where u is the input feature and v is the corresponding style feature. $\mu(u)$ and
 $\sigma(u)$ compute the mean and variance of feature u , respectively. $\sigma(v)$ and $\mu(v)$
 245 are the learned scale and bias to modulate the normalized feature u .

Discussion. Instance normalization (IN) plays a crucial role in improving
 the generalization capability of IBN-Net. However, as mentioned above, IN
 dilutes the content discrimination. Unlike IBN-Net trained on Cityscapes, our
 approach deploys multiple environmental style images to train MuSe-Net. When
 there are significant discrepancies between these styles, we suggest that IN could
 diminish more useful information in order to learn compromise parameters for
 style alignment of features. Therefore, we propose an **adaptive adjustment**

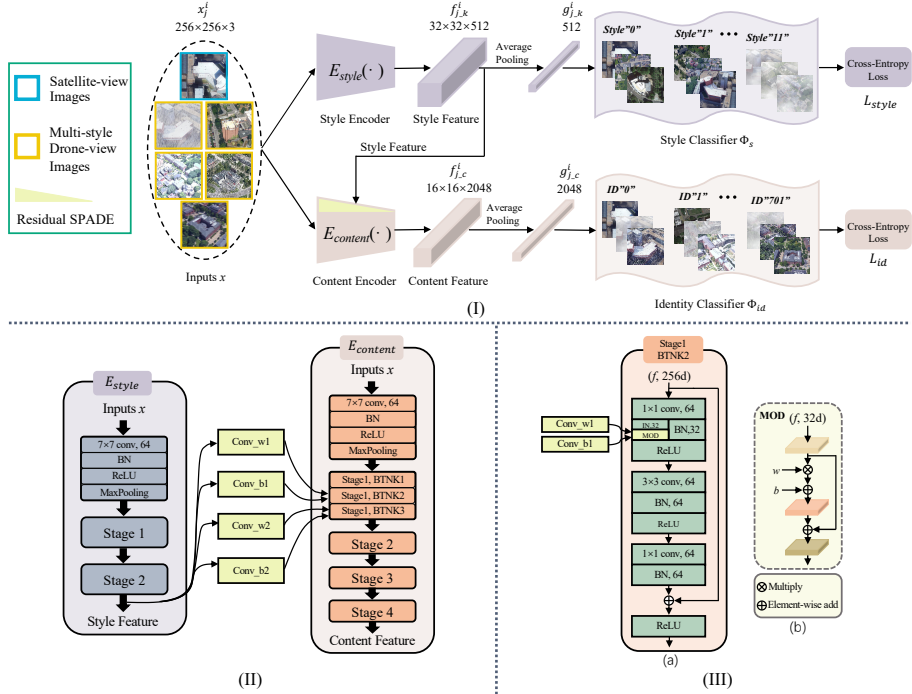


Figure 2: (I) A schematic overview of MuSe-Net. One batch of inputs contains the same number of satellite and drone images, and the style of satellite images is invariable. MuSe-Net consists of two branches. Purple blocks indicate the multiple-environment style extraction branch (purple branch), and pink blocks denote the self-adaptive feature extraction branch (pink branch). The purple branch is employed to group the same style features. Then style features extracted from the style encoder are fed into Residual SPADE. Residual SPADE is embedded into the content encoder, which belongs to the pink branch. The pink branch is applied to narrow down the distance of inputs with the same geo-tag. (II) Detailed demonstration of information interaction between the style encoder and the content encoder. The extracted style information is first convolved to produce the modulation parameters in Residual SPADE. After that, we utilize the learned modulation parameters to modulate middle features of inputs in the content encoder. (III) Illustration of the location of Residual SPADE in one bottleneck of the content encoder (a) and the calculation flow of the modulation operation (b). In Residual SPADE, a group of modulation parameters w and b comes from two convolutional layers, *i.e.*, Conv_w1 and Conv_b1. Afterwards the learned w and b are applied to modulate the activation of instance normalization (IN).

strategy of style information which inserts the Spatially-adaptive denormalization (SPADE) after IN and employs the style information of images as the external condition to dynamically adjust the activation of IN. It is worth noting that we do not directly follow Equation 1 to modulate the normalized activations. We reserve the affine parameters of IN and apply a residual structure to adjust the feature. We call the modified SPADE as **Residual SPADE**, which can be formulated as:

$$\begin{aligned}
 R_SPADE(u, v) &= \sigma(v) \cdot IN(u) + \mu(v) + IN(u) \\
 &= IN(u) \cdot (1 + \sigma(v)) + \mu(v),
 \end{aligned}
 \tag{2}$$

where R_SPADE denotes Residual SPADE. Characters u , v , $\sigma(v)$ and $\mu(v)$ have the same meaning as in Equation 1, $IN(\cdot)$ is the operation of instance normalization. R_SPADE is a generalization of IN . When the learned parameters $\sigma(v)$ and $\mu(v)$ converge to zero, R_SPADE can arrive at IN . Compared with Equation 1, R_SPADE has a residual structure that has been shown to facilitate the learning of network parameters [21]. With the dynamic fine-tuning by R_SPADE , the final depth features tend to retain the discrimination as much as possible while reducing the interference of their respective styles. Experiments in Section 4 demonstrate the effectiveness of MuSe-Net.

3.3. Overview of MuSe-Net

The proposed Multiple-environment Self-adaptive Network (MuSe-Net) is illustrated in Figure 2 (I). MuSe-Net consists of two branches: the multiple-environment style extraction branch and the self-adaptive feature extraction branch. These two branches have the same inputs. The multiple-environment style extraction branch is employed to extract features with different style information. Then these style features as the control data are fed into Residual SPADE to conduct a learnable transformation. Subsequently, the self-adaptive feature extraction branch employs the learned affine parameters of Residual SPADE to dynamically align the style information of inputs and pulls the content features with the same identity together.

The multiple-environment style extraction branch. This branch has two components: a style encoder and a style classifier. The style encoder is intercepted from ResNet-50 [21]. In particular, ResNet-50 contains four stages with repeated bottlenecks named stage1, stage2, stage3 and stage4. Following the analysis [18] that the style discrepancy is mostly preserved in shallow layers, we pick the first two stages of ResNet-50 as the style encoder to extract the style feature, as shown in Figure 2 (II). The style classifier consists of a batch normalization layer (BN), a dropout layer (Dropout), and a fully-connected layer (FC). Given an aerial-view image x_j^i (*i.e.*, drone or satellite) of size $256 \times 256 \times 3$, we first utilize the style encoder to acquire the style feature f_{j-k}^i with the shape of $32 \times 32 \times 512$. Then we employ the average pooling layer to transform f_{j-k}^i into a 512-dim feature g_{j-k}^i . In the end, we deploy the style classifier to predict the style of the input and utilize the cross-entropy loss to optimize this branch. The above process could be formulated as:

$$f_{j-k}^i = E_{style}(x_j^i), \quad (3)$$

$$g_{j-k}^i = Avgpool(f_{j-k}^i), \quad (4)$$

$$p(y_{style}^i | x_j^i) = softmax(\Phi_s(g_{j-k}^i)), \quad (5)$$

$$L_{style} = \sum_{i,j} -\log(p(y_{style}^i | x_j^i)), \quad (6)$$

where Φ_s denotes the style classifier. $p(y_{style}^i | x_j^i)$ is the predicted probability of x_j^i belonging to the corresponding style label y_{style}^i . In Equation 6, we calculate the cross-entropy loss.

The self-adaptive feature extraction branch. This branch consists of a content encoder with Residual SPADE embedded and an identity classifier. The content encoder is proposed relying on IBN-Net [18]. IBN-Net has the similar structure with ResNet-50. Specifically, the number of bottlenecks in stage1 of IBN-Net is 3. We embed Residual SPADE in the second and last bottlenecks

of stage1 as the content encoder (see Figure 2 (II)). Residual SPADE contains two convolutional layers, *i.e.*, Conv_w1 and Conv_b1. One convolutional layer is employed to learn the scale, and another is for the bias (see Figure 2 (III)). The identity classifier has the same component with the style classifier, *i.e.*, a batch normalization layer (BN), a dropout layer (Dropout), and a fully-connected layer (FC). The content encoder accepts the same input x_j^i with the style encoder, and is employed to extract the content feature f_{j-c}^i of size $16 \times 16 \times 2048$. Residual SPADE serves as an important role in the content encoder. In Residual SPADE, the style feature f_{j-k}^i is first interpolated to the same size as the activation of instance normalization (IN) in the content encoder. Then the interpolated feature is convolved to produce the scale and bias to modulate the activation of IN, and the modulation operation is shown in Figure 2 (III-b). The extracted content feature is further transformed into a 2048-dim feature g_{j-c}^i by an average pooling layer. Finally, we harness the identity classification loss as the proxy target to force the content encoder to extract the discriminative feature, and this loss can be formulated as:

$$p(y_{ID}^i|x_j^i) = softmax(\Phi_{ID}(g_{j-c}^i)), \quad (7)$$

$$L_{ID} = \sum_{i,j} -\log(p(y_{ID}^i|x_j^i)), \quad (8)$$

where Φ_{ID} indicates the identity classifier. $p(y_{ID}^i|x_j^i)$ is the predicted probability that x_j^i belongs to the geo-tagged identity label y_{ID}^i .
270

Optimization. We train MuSe-Net by jointly employing the style loss L_{style} and the identity loss L_{ID} :

$$L_{total} = L_{style} + L_{ID}. \quad (9)$$

The style loss forces features with different style information to stay apart, and the identity loss brings matching image pairs of the same geo-tag closer. Also, the identity loss serves the optimization of Residual SPADE.

The pseudocode for MuSe-Net is shown as Algorithm 1.

Algorithm 1 PyTorch-style pseudocode for MuSe-Net.

```
# model: MuSe_Net
# N: The batch size of one platform, \ie, drone or satellite.
# style_list: A list containing 10 transformations of the environmental style
.
# x: The input image.
# X: One batch of input images.
# ys: The style label which belongs to [0, 10]. The style label of all
    satellite images is 0. The style labels of drone images are determined
    by the index of the style transformations in the style_list. For
    instance, the index of the rain style is 2, then the style label of a
    rain-style drone image is 3, \ie, index + 1.
# Ys: One batch of ys
# yi: The identity label of cross-platform geo-localization images.
# Yi: One batch of yi.
# CE: The cross entropy loss.
# _s: The satellite platform.
# _d: The drone platform.
# _sty: The images with environmental styles.
for data_s, data_d in loader_s, loader_d: # load a satellite batch and a
    drone batch with N samples, separately.
    X_s, Yi_s = data_s
    X_d, Yi_d = data_d
    X_d_sty = []
    Ys_d = []

    for x_d in X_d:
        generator, ys_d = random_select(style_list) # generator is a function
            of the style transformation, and ys_d is the corresponding
            style label.
        x_d_sty = generator(x_d)
        X_d_sty.append(x_d_sty)
        Ys_d.append(ys_d)
    X_s_sty = X_s
    Ys_s = [0] * N

    Yi_s', Yi_d', Ys_s', Ys_d' = model(X_s_sty, X_d_sty) # The outputs are the
        prediction vectors
    sty_loss = CE(Ys_s', Ys_s) + CE(Ys_d', Ys_d) # Equation (6)
    id_loss = CE(Yi_s', Yi_s) + CE(Yi_d', Yi_d) # Equation (8)
    loss = id_loss + sty_loss

# optimization step
loss.backward()
optimizer.step()
```

275 4. Experiments

We first introduce two datasets used for MuSe-Net and the evaluation protocol in Section 4.1. Then we describe the implementation details in Section 4.2. The comparison of results with different methods is provided in Section 4.3, and the model analysis is followed in Section 4.4.

280 4.1. Datasets and Evaluation Protocol

We mainly train and evaluate the proposed method using the University-1652 [1] since it supports large-scale cross aerial-view images. We also verify the effectiveness of our method in SUES-200 [23] and CVUSA [24].

University-1652 [1] is a newly-released dataset that focuses on the drone-based geo-localization. It consists of data from three different platforms, *i.e.*,
285 drones, satellites, and phone cameras. All of these data are collected from 1,652 buildings of 72 universities around the world. There are 54 drone-view images for one building in the dataset to guarantee that the drone-view data can cover rich information of the target, *e.g.*, scale and viewpoint variants. With one
290 satellite-view image for each building as a reference, the dataset also includes 5,580 street-view images. Due to the limited viewpoint of the phone camera, street-view images can not cover all facets of a target building. To make up this weakness as much as possible, 21,099 common-view images from Google Image are added to University-1652 as an extra training set. The training set includes
295 701 buildings of 33 universities, and another 951 buildings belonging to the rest 39 universities are contained in the test set. Universities in the training and test set are not overlapping. The dataset support two new tasks, *i.e.*, drone-view target localization (Drone \rightarrow Satellite) and drone navigation (Satellite \rightarrow Drone). In the drone-view target localization task, the query set contains 37,855
300 drone-view images, and the gallery set includes 701 true-matched satellite-view images and 250 distractors. For the drone navigation task, with 701 satellite-view images as the query set, there are 37,855 true-matched drone-view images and 13,500 distractors in the gallery. Under this task, one query image has

multiple correct matches in the gallery. It is clear that the drone-view target
305 localization is a more challenging task than drone navigation since there is only
one true-matched satellite-view image for a drone-view query.

SUES-200 [23] is a multi-height, multi-scene dataset which considers geo-
localization between drone and satellite platforms. The dataset contains 200
scenes, and the drone-view images are recorded at four different heights: 150m,
310 200m, 250m, and 300m. At each height, one satellite-view scene corresponds to
50 drone-view images. It is worth noting that all drone-view images in SUES-200
are captured by a drone in real-world scenes.

CVUSA [24] consists of image pairs from two viewpoints, *i.e.*, the street
view and the satellite view. Each viewpoint contains 35,532 images for training
315 and 8,884 images for testing. It is worth noting that street-view images are
panoramas, and all the street and satellite images are north aligned.

Evaluation protocol. The performance of our method is evaluated by the
Recall@K (**R@K**) and the average precision (**AP**). **R@K** denotes the propor-
tion of correctly localized images in the top-K list, and **R@1** is an important
320 indicator. **AP** is equal to the area under the Precision-Recall curve. Higher
scores of **R@K** and **AP** indicate better performance of the network.

4.2. Implementation Details

The style encoder is intercepted from ResNet-50 [21] and initialized using
the pre-trained weights on ImageNet [54]. The kernel size of the convolutional
325 layer in Residual SPADE is 3×3 , and the kernel is initialized with *normal*
initialization. We employ weights of IBN-Net50-a [18] which is trained on Im-
ageNet [54] to initialize the content encoder. Following [1], the stride of the
second convolutional layer and the last down-sample layer of the first bottle-
neck in stage4 of the content encoder is modified from 2 to 1. We fix the size
330 of input images to 256×256 pixels when training and inference. In training,
we augment satellite-view images by employing random cropping and flipping.
For drone-view images, we first apply the library of *imgaug* [15] to change the
environmental style of images. For instance, we aim to generate an image in

overexposure. We need to first convert a RGB image into the NumPy format
335 using `img = np.array(img)`. Then we process the image in NumPy format
using the following codes:

```
# img: The input image
# img1: The input image in numpy format
# img2: The output image with overexposure style
340 # mul, add: Two parameters that control the brightness of the
      image
import numpy as np
import imgaug as iaa
img1 = np.array(img)
345 aug = iaa.MultiplyAndAddToBrightness(mul=1.6, add=(0,30),
      seed=1992)
img2 = aug(image = img1).
```

The random cropping and flipping are subsequently performed to enhance these
generated drone-view images. We adopt stochastic gradient descent (SGD) with
350 momentum 0.9 and weight decay 0.0005 to optimize our model. The mini-batch
of training is set to 16 with 8 images for one platform. The initial learning rate
is 0.005 for two classifiers and Residual SPADE, and 0.0005 for the rest layers.
Our model is trained for 210 epochs, and the learning rate is decayed to its
0.1 and 0.01 at 120 and 180 epochs. During testing, the Euclidean distance is
355 applied to measure the similarity between the query and candidate images in
the gallery. We implement our code based on Pytorch [55], and all experiments
are conducted on one NVIDIA RTX 2080Ti GPU. Our model takes 2 hours,
4 minutes and 59 seconds to train in University-1652. For one environmental
condition, the testing time of Drone \rightarrow Satellite and Satellite \rightarrow Drone are 4
360 minutes, 52 seconds and 5 minutes, 44 seconds, respectively.

4.3. Comparisons with Competitive Methods

Results on University-1652. University-1652 [1] supports two tasks:
drone-view target localization (Drone \rightarrow Satellite) and drone navigation (Satel-
lite \rightarrow Drone). We re-implement seven methods as competitive comparisons of
365 our method on these two tasks. Seven comparison methods include only the fea-
ture extraction branch containing a content encoder and an identity classifier.

Content encoders in seven comparison methods are VGG16 [56], ResNet-50 [21] (Zheng *et al.* [1]), ResNet-101 [21], DenseNet121 [20], Swin-T [57], IBN-Net50-a (IBN-Net [18]), and LPN [2]. Both Swin-T [57] and LPN [2] were published
370 in 2021. Keeping the style of satellite-view images unchanged, the results of drone-view images in 10 different conditions are shown in Table 1. In seven re-implemented methods of Drone \rightarrow Satellite, LPN [2] explicitly considers the local information and obtains the best results. Excluding LPN, we observe that IBN-Net [18] has significantly improved geo-localization performance. Our
375 method surpasses IBN-Net [18] in all environmental conditions. Specifically, when calculating the mean accuracy, our method improves the R@1 accuracy from 62.30% to 65.15% (+2.85%) and the AP accuracy from 66.46% to 69.16% (+2.70%). Meanwhile, our method also exceeds LPN [2]. The Satellite \rightarrow Drone is an easier task than Drone \rightarrow Satellite. We first observe that even
380 VGG16 can obtain higher performance of R@1 than the reported results of our method in Drone \rightarrow Satellite. In Satellite \rightarrow Drone, our method still keeps sufficient advantages over six comparison methods that do not utilize local information. In particular, our results in 10 different environmental conditions outperform all of the IBN-Net [18], and the mean accuracy of R@1 increases
385 from 82.27% to 84.68% (+2.41%) and the mean value of AP raises from 63.36% to 65.75% (+2.39%). Besides, our method is still competitive compared to LPN. The experimental results of two sub-tasks demonstrate two points. First, as the multiple-domain related method, IBN-Net [18] compared with other comparison methods with the same feature treatment can acquire a more robust representation containing less domain shift caused by different environmental styles.
390 Second, our method based on IBN-Net learns the dynamic parameters to adaptively adjust the style information and can further improve the performance, as discussed in Section 3.2. It is worth noting that our performance is still impacted by different environments, and some scenes have heavy invisibility, such
395 as buildings in fog or dark. Our method minimizes the prediction discrepancy between the target weathers and normal cases. We intend to relieve the negative impact of the noisy environment to improve the robustness.

Table 1: The R@1(%) and AP(%) accuracy for drone-view target localization task (Drone \rightarrow Satellite) and drone navigation task (Satellite \rightarrow Drone) on University-1652. In these two tasks, drone-view images hold 10 different environmental styles, and the style of satellite-view images is constant. The best results are in bold.

Method	Normal		Fog		Rain		Snow		Fog +Rain		Fog +Snow		Rain +Snow		Dark		Over-exposure		Wind		Mean \uparrow	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP		
Drone \rightarrow Satellite																						
VGG16 [56]	59.98	64.69	56.21	61.11	53.97	58.90	50.07	55.08	50.43	55.63	42.77	48.01	51.08	56.10	39.10	44.30	45.16	50.47	50.84	56.05	49.96	55.03
Zheng <i>et al.</i> [1]	67.83	71.74	60.97	65.23	60.29	64.61	55.58	60.09	54.75	59.40	44.85	49.78	57.61	62.03	39.70	44.65	51.85	56.75	58.28	62.83	55.17	59.71
ResNet-101 [21]	70.07	73.04	63.87	68.22	63.34	67.59	59.75	64.15	57.45	62.12	48.31	53.28	60.25	64.68	46.12	51.02	56.34	61.23	62.13	66.63	58.76	63.29
DenseNet121 [20]	69.48	73.26	64.25	68.47	63.47	67.64	59.29	63.70	59.68	64.13	50.41	55.20	60.21	64.57	48.57	53.41	54.04	58.88	60.74	65.14	59.01	63.44
Swin-T [57]	69.27	73.18	66.46	70.52	65.44	69.60	61.79	66.23	63.96	68.21	56.44	61.07	62.68	67.02	50.27	55.18	55.46	60.29	63.81	68.17	61.56	65.95
IBN-Net [18]	72.35	75.85	66.68	70.64	67.95	71.73	62.77	66.85	62.64	66.84	51.09	55.79	64.07	68.13	50.72	55.53	57.97	62.52	66.73	70.68	62.30	66.46
LPN [2]	74.33	77.60	69.31	72.95	67.96	71.72	64.90	68.85	64.51	68.52	54.16	58.73	65.38	69.29	53.68	58.10	60.90	65.27	66.46	70.35	64.16	68.14
Ours	74.48	77.83	69.47	73.24	70.55	74.14	65.72	69.70	65.59	69.64	54.69	59.24	66.64	70.55	53.85	58.49	61.05	65.51	69.45	73.22	65.15	69.16
Satellite \rightarrow Drone																						
VGG16 [56]	75.89	58.50	75.18	55.42	71.61	53.03	68.19	48.29	71.18	49.34	65.48	40.87	69.47	50.03	64.34	35.74	64.91	44.20	68.90	49.53	69.52	48.50
Zheng <i>et al.</i> [1]	83.45	67.94	79.60	61.12	77.60	59.73	73.18	55.07	75.89	54.45	70.76	43.26	74.75	56.44	69.47	39.25	72.18	51.91	76.46	57.59	75.33	54.68
ResNet-101 [21]	85.73	71.79	82.45	66.46	81.46	65.68	79.74	61.72	79.74	60.59	74.75	50.31	80.17	62.61	75.32	45.37	79.60	58.21	82.31	64.67	80.13	60.74
DenseNet121 [20]	83.74	70.34	82.31	66.32	81.17	65.23	78.60	60.33	79.46	61.66	74.61	51.14	78.46	61.68	74.47	47.88	74.32	55.26	78.32	61.63	78.55	60.15
Swin-T [57]	80.74	68.94	81.03	67.46	81.17	66.39	78.46	61.33	79.17	64.65	74.89	56.57	78.89	63.49	75.61	48.43	76.60	56.57	78.74	64.45	78.53	61.83
IBN-Net [18]	86.31	73.54	84.59	67.61	84.74	69.03	80.88	64.44	83.31	63.71	77.89	52.14	83.02	65.74	78.46	50.77	79.46	58.64	84.02	67.94	82.27	63.36
LPN [2]	87.02	75.19	86.16	71.34	83.88	69.49	82.88	65.39	84.59	66.28	79.60	55.19	84.17	66.26	82.88	52.05	81.03	62.24	84.14	67.35	83.64	65.08
Ours	88.02	75.10	87.87	69.85	87.73	71.12	83.74	66.52	85.02	67.78	80.88	54.26	84.88	67.75	80.74	53.01	81.60	62.09	86.31	70.03	84.68	65.75

Results on SUES-200. The drone-view images on SUES-200 are divided into four groups according to the collected heights. We choose the hardest group, the drone-view images at 150m height, to conduct experiments. In experiments, the normal drone-view images are acquired in real environments, while other environmental images are synthesized on the basis of the normal situation. The results of our method are shown in Tabel 2. We observe a similar phenomenon as for experiments on University-1652. We mainly compare our method with IBN-Net [18]. Our method improves the mean accuracy of R@1 from 39.58% to 41.59% (+2.01%) and increases the mean value of AP from 46.23% to 48.53% (+2.30%) in Drone \rightarrow Satellite. In Satellite \rightarrow Drone, our method raises the mean accuracy of R@1 from 52.25% to 53.38% (+1.13%) and goes up the mean value of AP from 37.78% to 39.20% (+1.42%). The effective performance improvement lays the foundation for geo-localization in realistic multiple environments.

Results on CVUSA. Street-view and satellite-view images on CVUSA [24] retain drastic appearance changes. In order to achieve cross-view images with a similar pattern, we follow [8, 6] to pre-process satellite-view images before training and testing. Specially, we apply the polar transform to warp satellite

Table 2: The R@1(%) and AP(%) accuracy for drone-view target localization task (Drone → Satellite) and drone navigation task (Satellite → Drone) on SUES-200. In these two tasks, drone-view images from 150m height hold 10 different environmental styles, and the style of satellite-view images is constant. The best results are in bold.

Method	Normal		Fog		Rain		Snow		Fog +Rain		Fog +Snow		Rain +Snow		Dark		Over-exposure		Wind		Mean ↑	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP
Drone → Satellite																						
Zheng <i>et al.</i> [1]	41.28	48.01	36.92	43.17	39.38	45.41	31.22	38.05	32.58	38.55	20.55	25.84	34.08	40.61	35.15	41.43	27.67	33.55	35.17	41.67	33.40	39.63
IBN-Net [18]	48.55	54.91	43.83	50.21	42.88	49.54	37.78	44.78	39.50	45.77	24.82	31.47	39.62	46.55	39.20	46.41	34.83	41.39	44.78	51.23	39.58	46.23
Ours	50.05	57.26	46.90	53.69	45.12	51.99	43.97	50.92	40.42	47.17	25.40	31.74	43.45	50.52	39.72	47.01	32.75	39.81	48.15	55.14	41.59	48.53
Satellite → Drone																						
Zheng <i>et al.</i> [1]	52.50	40.75	48.75	34.23	48.75	35.16	45.00	29.69	45.00	28.21	42.50	18.22	45.00	31.19	45.00	33.32	42.50	23.47	42.50	31.52	45.75	30.58
IBN-Net [18]	55.00	45.10	51.25	41.66	55.00	39.86	47.50	37.37	50.00	35.16	41.25	23.85	53.75	38.30	53.75	39.71	55.00	33.33	60.00	43.48	52.25	37.78
Ours	58.75	48.10	56.25	44.71	51.25	42.13	52.50	40.78	48.75	37.66	38.75	24.23	53.75	40.74	52.50	35.38	60.00	31.96	61.25	46.35	53.38	39.20

Table 3: The R@1(%) and AP(%) performance of geo-localization on CVUSA. In this task, street-view images as queries have 10 different environmental style variations, while the style of satellite-view images in the gallery is constant. The best results are in bold.

Method	Normal		Fog		Rain		Snow		Fog +Rain		Fog +Snow		Rain +Snow		Dark		Over-exposure		Wind		Mean ↑	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP
Zheng <i>et al.</i> [1]	63.78	67.77	60.19	64.47	61.53	65.65	61.39	65.52	58.00	62.27	55.32	59.72	60.81	65.03	51.64	55.91	59.89	64.14	60.41	64.69	59.30	63.52
IBN-Net [18]	76.61	79.50	74.68	77.80	75.52	78.52	74.54	77.65	73.31	76.61	71.33	74.71	74.72	77.80	66.45	69.99	73.14	76.29	74.63	77.76	73.49	76.66
Ours	78.04	80.85	75.75	78.75	77.04	79.96	76.47	79.38	74.82	77.85	71.87	75.23	76.50	79.44	67.95	71.42	74.92	78.01	76.59	79.47	75.00	78.04

images, which ensures that the appearance of satellite images is closer to street-view panoramas. In the multiple-environment setting, the satellite-view image is unchanged, and we only generate the multi-domain street-view images (see Figure 3). Results of our method compared with two competitive methods on CVUSA are detailed in Table 3. We could observe that our method obtains the increment in most environmental conditions than IBN-Net [18]. Meanwhile, the mean accuracy of R@1 goes up from 73.49% to 75.00% (+1.51%), and the mean accuracy of AP boosts from 76.66% to 78.04% (+1.38%).

Results on unseen weather. In the realistic scenario, the aerial-view geo-localization system can usually encounter the unseen weather. To explore whether MuSe-Net can cope with these weather conditions, especially the severe weather, we carry out experiments on mixing fog, rain and snow. Table 4 shows the experimental results. The proposed MuSe-Net on University-1652 [1] has achieved 44.10% R@1 accuracy and 48.95% AP for Drone → Satellite, and 75.32% R@1 accuracy and 44.49% AP for Satellite → Drone. The obtained R@1 accuracy and AP on CVUSA are 68.29% and 71.81%, respectively. The superior

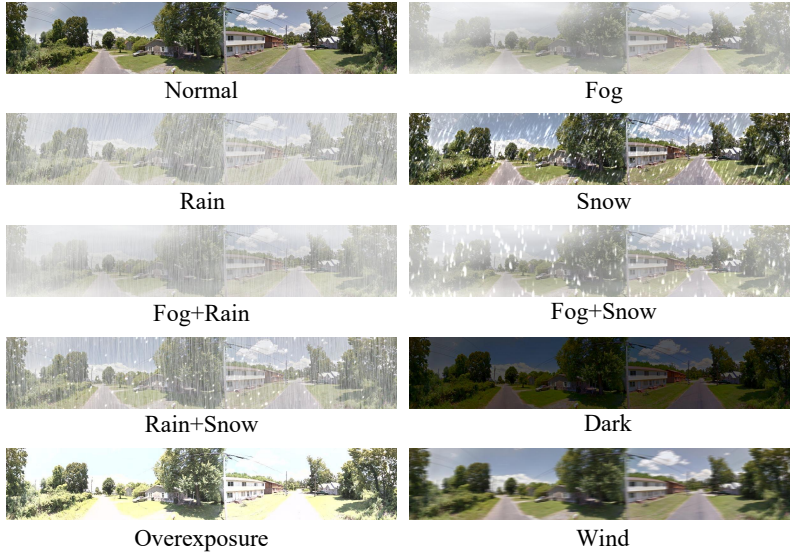


Figure 3: Examples of a street-view panorama and its synthesized environments on CVUSA [24].

performance compared with two competitive methods, *i.e.*, Zheng *et al.* [1] and IBN-Net [18], suggests that our method holds great potential to the unseen extreme weather. This character can also provide additional assurance of safe flight.

4.4. Model Analysis

We further analyze and discuss our model based on the multiple-environment drone-view target localization task (Drone \rightarrow Satellite) in this section.

IBN-Net vs SPADE vs Residual SPADE. As discussed in Section 3.2, applying the adaptive adjustment strategy of style information (*i.e.*, IBN-Net [18] + SPADE [22]) can retain more discriminative features than IBN-Net when retrieval in different environments. Meanwhile, the proposed Residual SPADE with a residual structure is more effective than SPADE [22]. The experiments are shown in Table 5. We observe first that IBN-Net combined with SPADE acquires a superior performance than only IBN-Net in all 10 different environments. Besides, Residual SPADE achieves higher results than SPADE in 7

Table 4: Results of retrieving in an unseen extreme weather, *i.e.*, fog, rain and snow mixed.

Method	Fog + Rain + Snow					
	University-1652				CVUSA	
	Drone → Satellite		Satellite → Drone		Street → Satellite	
	R@1	AP	R@1	AP	R@1	AP
Zheng <i>et al.</i> [1]	27.73	32.35	61.34	27.43	46.31	51.03
IBN-Net [18]	41.19	46.06	73.75	42.57	67.24	70.98
Ours	44.10	48.95	75.32	44.49	68.29	71.81

Table 5: Ablation study of IBN-Net combined with SPADE and Residual SPADE, respectively.

The best mean results are in bold.

Method	Normal		Fog		Rain		Snow		Fog + Rain		Fog + Snow		Rain + Snow		Dark		Over-exposure		Wind		Mean ↑	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP
IBN-Net [18]	72.35	75.85	66.68	70.64	67.95	71.73	62.77	66.85	62.64	66.84	51.09	55.79	64.07	68.13	50.72	55.53	57.97	62.52	66.73	70.68	62.30	66.46
+ SPADE [22]	74.51	77.88	67.70	71.65	68.60	72.55	64.61	68.76	63.93	68.20	53.80	58.51	65.76	69.86	53.91	58.62	58.94	63.55	68.41	72.36	64.02	68.19
+ Residual SPADE	74.48	77.83	69.47	73.24	70.55	74.14	65.72	69.70	65.59	69.64	54.69	59.24	66.64	70.55	53.85	58.49	61.05	65.51	69.45	73.22	65.15	69.16

environmental conditions. In the remaining environments (*i.e.*, Normal, Dark and Wind), Residual SPADE also acquires similar results to SPADE. When considering the mean result, Residual SPADE goes up the R@1 accuracy from 64.02
450 to 65.15 (+1.13%) and increases the AP value from 68.19 to 69.16 (+0.97%). The significant performance improvement further certifies the effectiveness of the adaptive adjustment strategy of style information and Residual SPADE.

Which bottleneck(s) embedding Residual SPADE is more effective? As mentioned in Section 3.3, we embed Residual SPADE in the second
455 and last bottlenecks of stage1. Other embedding options exist. Work [18] proves that the style difference mostly lies in the shallow layers. Following this finding, we select all three bottlenecks in stage1 for objects of our study. Specifically, we conduct experiments that embedding single, double or three Residual SPADE in these selected bottlenecks. Table 6 shows the details of experimental results. We
460 observe first that deploying Residual SPADE in any bottlenecks yields higher mean results than IBN-Net [18] showed in Table 1, which demonstrates the effectiveness of Residual SPADE. Then we compare results of deploying the single Residual SPADE in three different bottlenecks (*i.e.*, the first three rows of

Table 6: Results of embedding Residual SPADE in different IBN bottlenecks. **S** denotes the stage, and **B** stands for the bottleneck. For instance, **S1-B2,B3** means that the second and third IBN bottlenecks of stage1 are embedded with Residual SPADE. The best mean results are in bold.

Method	Normal		Fog		Rain		Snow		Fog +Rain		Fog +Snow		Rain +Snow		Dark		Over -exposure		Wind		Mean ↑	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP
S1-B1	73.76	77.13	69.02	72.79	69.26	72.98	64.44	68.48	64.57	68.67	54.12	58.17	66.27	70.18	52.71	57.34	59.93	64.42	67.33	71.21	64.14	68.14
S1-B2	73.74	77.20	68.69	72.56	69.17	72.93	65.51	69.54	64.53	68.71	54.63	59.26	66.61	70.52	53.96	58.57	59.53	64.08	68.45	72.26	64.48	68.56
S1-B3	74.28	77.69	68.91	72.79	68.74	72.61	64.09	68.29	64.58	68.77	54.05	58.78	66.00	70.01	52.79	57.56	59.33	63.95	68.05	72.05	64.08	68.25
S1-B1,B2	75.04	78.38	68.30	72.20	69.35	73.20	65.09	69.02	63.34	67.65	52.47	57.18	65.80	69.91	51.19	56.08	59.14	63.76	68.89	72.80	63.86	68.02
S1-B1,B3	73.99	77.46	68.28	72.30	69.33	73.17	64.63	68.92	64.05	68.39	52.95	57.83	65.77	69.94	51.40	56.33	58.49	63.22	67.88	71.95	63.68	67.95
S1-B2,B3	74.48	77.83	69.47	73.24	70.55	74.14	65.72	69.70	65.59	69.64	54.69	59.24	66.64	70.55	53.85	58.49	61.05	65.51	69.45	73.22	65.15	69.16
S1-B1,B2,B3	74.85	78.15	68.12	72.02	68.94	72.77	65.91	69.95	62.81	67.06	53.57	58.35	66.46	70.49	52.58	57.41	59.27	63.87	68.57	72.45	64.11	68.25

Table 7: Ablation study of two losses applying different weight ratios. The best mean results are in bold.

$L_{ID} : L_{style}$	Normal		Fog		Rain		Snow		Fog +Rain		Fog +Snow		Rain +Snow		Dark		Over -exposure		Wind		Mean ↑	
	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP	R@1	AP
1 : 0.5	73.67	77.10	67.47	71.42	68.75	72.59	65.11	69.15	63.54	67.74	54.47	59.22	65.93	69.95	52.32	56.98	58.45	63.02	67.97	71.85	63.77	67.90
1 : 1	74.48	77.83	69.47	73.24	70.55	74.14	65.72	69.70	65.59	69.64	54.69	59.24	66.64	70.55	53.85	58.49	61.05	65.51	69.45	73.22	65.15	69.16
1 : 2	72.93	76.46	67.33	71.32	68.17	72.04	63.29	67.52	62.77	67.07	51.99	56.81	64.54	68.72	51.23	56.06	57.57	62.31	66.68	70.72	62.65	66.90
1 : 5	73.05	76.59	66.89	70.91	67.71	71.66	63.38	67.61	62.57	66.84	52.54	57.35	64.51	68.68	51.04	55.86	57.89	62.51	67.31	71.37	62.69	66.94

Table 6). Looking at mean results, embedding Residual SPADE in the second bottleneck ($S1 - B2$) achieves the best performance. When employing two or three Residual SPADE in bottlenecks, we notice that combinations containing the first bottleneck, *i.e.*, $S1 - B1, B2$, $S1 - B1, B3$ and $S1 - B1, B2, B3$, achieve slightly lower mean results than $S1 - B2, B3$. Finally, considering both the individual results in 10 conditions and the mean results, we choose $S1 - B2, B3$ as the choice of our method.

Effect of the loss weights. MuSe-Net is a dual-branch network to disentangle the style and the localization information from drone-view images. The identity loss motivates the self-adaptive feature extraction branch to learn the **style-agnostic localization-aware** feature, while the style loss encourages the multiple-environment style extraction branch to learn the **style-aware localization-agnostic** feature. Since these two tasks are complementary and equally important, we set 1:1 as the default weight ratio of two losses. We further simply search other weight ratios of two losses, as shown in Table 7. The experimental results confirm that balanced identity/style losses give the best results.

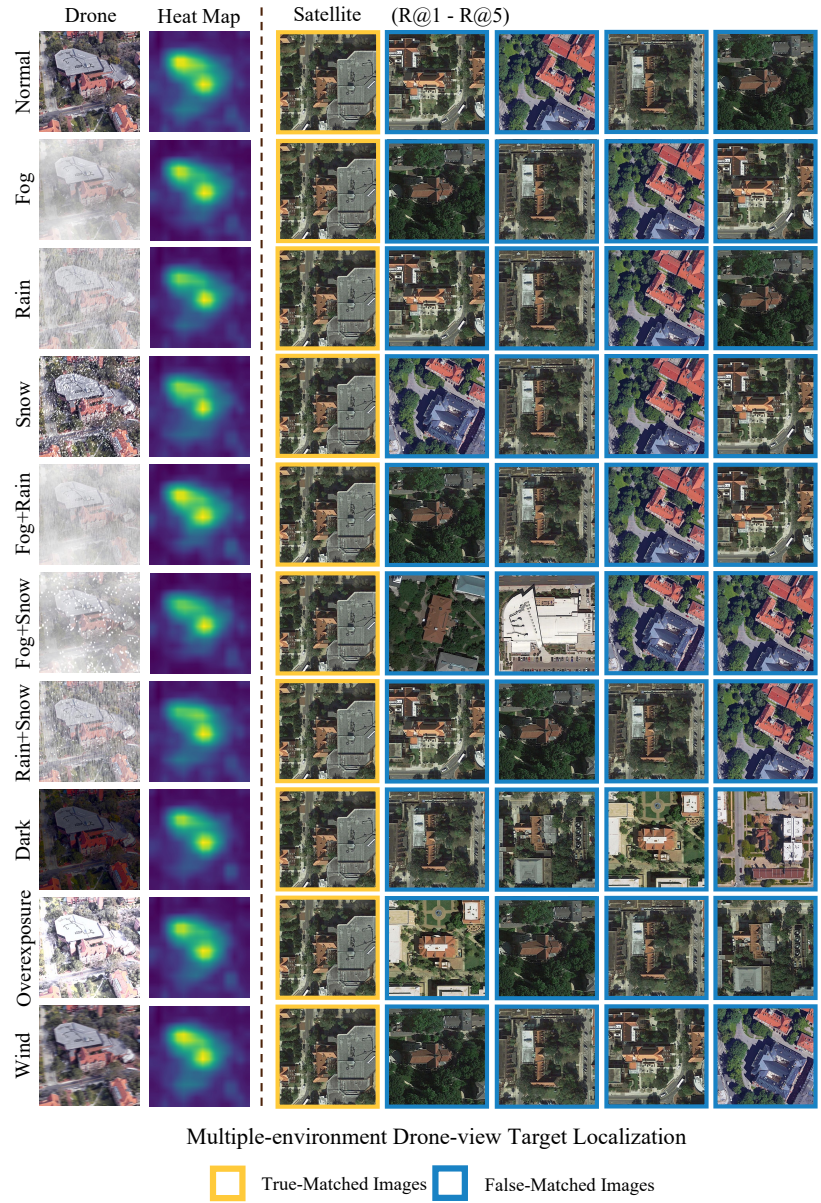


Figure 4: Visualization of heatmaps generated by our method and Top-5 retrieval results for a drone-view image in different conditions. The true matches are in yellow boxes, and the false matches are displayed in blue boxes.

Qualitative result. As shown in Figure 4, we visualise heatmaps and Top-5 retrieval results generated by our method in 10 different environmental conditions. Heatmaps show that our method can activate two regions of the geographic target. Another discovery is that there are subtle differences in the extent and brightness of the activated areas in 10 heatmaps. This phenomenon reflects from the side that results of geo-localization in 10 environmental conditions can exist difference. From the retrieval results shown, we observe that our model obtains the true match in the Top-1 yet the remaining retrieval results are inconsistent under 10 different conditions, which also indicates that the adjusted features still contain a few discrepancies.

Model complexity. We employ FLOPs and the parameter number to evaluate the model complexity of the proposed method and two baselines. FLOPs denotes the floating-point operations. The baseline methods of Zheng [1] and IBN-Net [18] have similar complexity, *i.e.*, 1.22×10^{10} FLOPs and 48.43million(M) parameter numbers. Our method inevitably yields a higher FLOPs (1.70×10^{10}) and parameter number (50.47 M) since the designed multiple-environment style extraction branch. However, the growth rates of FLOPs and the parameter number between baselines and our method are 39.34% and 4.21%, respectively. The lower costs of growth indicate that the complexity of our model is also acceptable. In addition, we also compare the parameter number of our method with ResNet-101 [21] based method, Swin-T [57] based method and LPN [2]. The parameter number of ResNet-101 based and Swin-T based method are 67.42 M and 53.14 M , respectively. The parameter number of LPN is 52.66 M . As shown in Table 1, we notice that our performance is still competitive even compared to networks with a larger parameter number.

5. Conclusion

In this paper, we identify the challenge when employing aerial-view geo-localization in the real-world scenario where the weather and illumination changes. To reduce domain gaps of different environments, we propose an end-to-end

510 learning network, called Multiple-environment Self-adaptive Network (MuSe-
Net), to dynamically adjust the style difference for inputs with one geo-tag.
MuSe-Net consists of two branches. One is a multiple-environment style ex-
traction network for learning environment-related information. The other is a
self-adaptive feature extraction network which integrates Residual SPADE into
515 the content encoder to dynamically balance the environmental domain shift. To
verify the effectiveness of MuSe-Net, we have evaluated the method in two drone-
based geo-localization dataset (*i.e.*, University-1652 [1] and SUES-200 [23]) and
achieved competitive performance. Besides, the proposed method also has ac-
quired competitive results on one street-to-satellite dataset, *i.e.*, CVUSA [24].
520 In the future, we will continue to study the disentangled representation learn-
ing and further improve the performance of geo-localization in realistic multiple
environments.

Data Availability Statement

Two datasets supporting the findings of this study are available with the
525 permission of the dataset authors. The links to request these datasets are as
follows.

- (1) University-1652 : <https://github.com/layumi/University1652-Baseline>;
- (2) CVUSA : <https://github.com/viibriddles/crossnet>.

References

- 530 [1] Z. Zheng, Y. Wei, Y. Yang, University-1652: A multi-view multi-source
benchmark for drone-based geo-localization, in: ACM International Con-
ference on Multimedia, 2020, doi: 10.1145/3394171.3413896.
- [2] T. Wang, Z. Zheng, C. Yan, J. Zhang, Y. Sun, B. Zheng, Y. Yang,
Each part matters: Local patterns facilitate cross-view geo-localization,
535 IEEE Transactions on Circuits and Systems for Video Technology-
Doi:10.1109/TCSVT.2021.3061265.

- [3] J. Lin, Z. Zheng, Z. Zhong, Z. Luo, S. Li, Y. Yang, N. Sebe, Joint representation learning and keypoint detection for cross-view geo-localization, *IEEE Transactions on Image Processing*.
- 540 [4] L. Liu, H. Li, Lending orientation to neural networks for cross-view geo-localization, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2019.
- [5] Y. Shi, X. Yu, L. Liu, T. Zhang, H. Li, Optimal feature transport for cross-view image geo-localization, in: *AAAI Conference on Artificial Intelligence*,
545 2020.
- [6] Y. Shi, X. Yu, D. Campbell, H. Li, Where am i looking at? joint location and orientation estimation by cross-view matching, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2020.
- [7] S. Hu, M. Feng, R. M. Nguyen, G. Hee Lee, Cvm-net: Cross-view matching network for image-based ground-to-aerial geo-localization, in: *IEEE*
550 *Conference on Computer Vision and Pattern Recognition*, 2018.
- [8] Y. Shi, L. Liu, X. Yu, H. Li, Spatial-aware feature aggregation for image based cross-view geo-localization, in: *Neural Information Processing Systems*, 2019.
- 555 [9] Z. Wu, X. Wang, J. E. Gonzalez, T. Goldstein, L. S. Davis, Ace: Adapting to changing environments for semantic segmentation, in: *IEEE International Conference on Computer Vision*, 2019.
- [10] N. T. S. Board, Aircraft accident investigative update, <https://www.nts.gov/investigations/Documents/DCA20MA059-Investigative-Update.pdf>
560 [pdf](https://www.nts.gov/investigations/Documents/DCA20MA059-Investigative-Update.pdf) (2020).
- [11] D. Li, Y. Yang, Y.-Z. Song, T. M. Hospedales, Deeper, broader and artier domain generalization, in: *IEEE International Conference on Computer Vision*, 2017.

- [12] P. Chattopadhyay, Y. Balaji, J. Hoffman, Learning to balance specificity
565 and invariance for in and out of domain generalization, in: European Conference on Computer Vision, 2020.
- [13] M. Ilse, J. M. Tomczak, C. Louizos, M. Welling, Diva: Domain invariant variational autoencoders, in: Medical Imaging with Deep Learning, 2020.
- [14] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley,
570 S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, Advances in neural information processing systems 27.
- [15] A. B. Jung, K. Wada, J. Crall, S. Tanaka, J. Graving, C. Reinders, S. Yadav, J. Banerjee, G. Vecsei, A. Kraft, Z. Rui, J. Borovec, C. Vallentin, S. Zhydenko, K. Pfeiffer, B. Cook, I. Fernández, F.-M. De Rainville, C.-
575 H. Weng, A. Ayala-Acevedo, R. Meudec, M. Laporte, et al., imgaug, <https://github.com/aleju/imgaug>, online; accessed 01-Feb-2020 (2020).
- [16] A. Khosla, T. Zhou, T. Malisiewicz, A. A. Efros, A. Torralba, Undoing the damage of dataset bias, in: European Conference on Computer Vision, 2012.
- 580 [17] D. Ulyanov, A. Vedaldi, V. Lempitsky, Improved texture networks: Maximizing quality and diversity in feed-forward stylization and texture synthesis, in: IEEE Conference on Computer Vision and Pattern Recognition, 2017.
- [18] X. Pan, P. Luo, J. Shi, X. Tang, Two at once: Enhancing learning and generalization capacities via ibn-net, in: European Conference on Computer
585 Vision, 2018.
- [19] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, in: International Conference on Machine Learning, 2015.

- 590 [20] G. Huang, Z. Liu, L. Van Der Maaten, K. Q. Weinberger, Densely connected convolutional networks, in: IEEE Conference on Computer Vision and Pattern Recognition, 2017.
- [21] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: IEEE Conference on Computer Vision and Pattern Recognition,
595 2016.
- [22] T. Park, M.-Y. Liu, T.-C. Wang, J.-Y. Zhu, Semantic image synthesis with spatially-adaptive normalization, in: IEEE Conference on Computer Vision and Pattern Recognition, 2019.
- [23] R. Zhu, L. Yin, M. Yang, F. Wu, Y. Yang, W. Hu, Sues-200: A multi-height
600 multi-scene cross-view image benchmark across drone and satellite, IEEE Transactions on Circuits and Systems for Video Technology 33 (9) (2023) 4825–4839. doi:10.1109/TCSVT.2023.3249204.
- [24] M. Zhai, Z. Bessinger, S. Workman, N. Jacobs, Predicting ground-level scene layout from aerial imagery, in: IEEE Conference on Computer Vision
605 and Pattern Recognition, 2017.
- [25] T.-Y. Lin, S. Belongie, J. Hays, Cross-view image geolocalization, in: IEEE Conference on Computer Vision and Pattern Recognition, 2013.
- [26] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al., Imagenet large scale visual
610 recognition challenge, International Journal of Computer Vision 115 (3) (2015) 211–252.
- [27] S. Workman, N. Jacobs, On the location dependence of convolutional neural network features, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015.
- 615 [28] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, Advances in neural information processing systems 25 (2012) 1097–1105.

- [29] B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, A. Oliva, Learning deep features for scene recognition using places database, *Neural Information Processing Systems Foundation* (2014) 487–495.
- [30] S. Workman, R. Souvenir, N. Jacobs, Wide-area image geolocalization with aerial reference imagery, in: *IEEE International Conference on Computer Vision*, 2015.
- [31] T.-Y. Lin, Y. Cui, S. Belongie, J. Hays, Learning deep representations for ground-to-aerial geolocalization, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2015.
- [32] R. Hadsell, S. Chopra, Y. LeCun, Dimensionality reduction by learning an invariant mapping, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2006.
- [33] S. Chopra, R. Hadsell, Y. LeCun, Learning a similarity metric discriminatively, with application to face verification, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2005.
- [34] Y. Tian, X. Deng, Y. Zhu, S. Newsam, Cross-time and orientation-invariant overhead image geolocalization using deep local features, in: *IEEE Winter Conference on Applications of Computer Vision*, 2020.
- [35] K. Regmi, M. Shah, Bridging the domain gap for ground-to-aerial image matching, in: *IEEE International Conference on Computer Vision*, 2019.
- [36] M. Dai, J. Hu, J. Zhuang, E. Zheng, A transformer-based feature segmentation and region alignment method for uav-view geo-localization, *IEEE Transactions on Circuits and Systems for Video Technology* 32 (7) (2022) 4376–4389. doi:10.1109/TCSVT.2021.3135013.
- [37] N. N. Vo, J. Hays, Localizing and orienting street views using overhead imagery, in: *European Conference on Computer Vision*, 2016.

- [38] S. Cai, Y. Guo, S. Khan, J. Hu, G. Wen, Ground-to-aerial image geo-
645 localization with a hard exemplar reweighting triplet loss, in: *IEEE International Conference on Computer Vision*, 2019.
- [39] Y. Lin, L. Zheng, Z. Zheng, Y. Wu, Z. Hu, C. Yan, Y. Yang, Improving
person re-identification by attribute and identity learning, *Pattern Recognition* 95 (2019) 151–161.
- 650 [40] B. Sun, G. Liu, Y. Yuan, F3-net: Multiview scene matching for drone-based
geo-localization, *IEEE Transactions on Geoscience and Remote Sensing* 61
(2023) 1–11. doi:10.1109/TGRS.2023.3278257.
- [41] H. Li, S. J. Pan, S. Wang, A. C. Kot, Domain generalization with adversarial
655 feature learning, in: *IEEE Conference on Computer Vision and Pattern Recognition*, 2018.
- [42] H. Li, Y. Wang, R. Wan, S. Wang, T.-Q. Li, A. C. Kot, Domain general-
ization for medical imaging classification with linear-dependency regular-
ization, in: *Neural Information Processing Systems*, 2020.
- [43] S. Chen, L. Wang, Z. Hong, X. Yang, Domain generalization by joint-
660 product distribution alignment, *Pattern Recognition* 134 (2023) 109086.
- [44] V. Vapnik, *The nature of statistical learning theory*, Springer science &
business media, 1999.
- [45] K. Zhou, Y. Yang, Y. Qiao, T. Xiang, Domain generalization with mixstyle,
in: *International Conference on Learning Representations*, 2021.
- 665 [46] H. Zhang, M. Cisse, Y. N. Dauphin, D. Lopez-Paz, mixup: Beyond empir-
ical risk minimization, in: *International Conference on Learning Representations*, 2018.
- [47] M. M. Rahman, C. Fookes, M. Baktashmotlagh, S. Sridharan, Correlation-
670 aware adversarial domain adaptation and generalization, *Pattern Recognition* 100 (2020) 107124.

- [48] J. Zhang, J. Song, Y. Yao, L. Gao, Curriculum-based meta-learning, in: ACM International Conference on Multimedia, 2021.
- [49] C. Finn, P. Abbeel, S. Levine, Model-agnostic meta-learning for fast adaptation of deep networks, in: International Conference on Machine Learning, 675 2017.
- [50] J. Zhang, L. Qi, Y. Shi, Y. Gao, Generalizable model-agnostic semantic segmentation via target-specific normalization, Pattern Recognition 122 (2022) 108292.
- [51] B. Zhang, Y. Tan, H. Wang, Z. Zhang, X. Zhou, J. Wu, Y. Mi, H. Huang, 680 W. Wang, Lsrml: A latent space regularization based meta-learning framework for mr image segmentation, Pattern Recognition (2022) 108821.
- [52] D. P. Kingma, M. Welling, Auto-encoding variational bayes, in: International Conference on Learning Representations, 2014.
- [53] Z. Zheng, X. Yang, Z. Yu, L. Zheng, Y. Yang, J. Kautz, Joint discriminative 685 and generative learning for person re-identification, in: IEEE Conference on Computer Vision and Pattern Recognition, 2019.
- [54] J. Deng, W. Dong, R. Socher, L. J. Li, K. Li, L. Fei-Fei, Imagenet: A large-scale hierarchical image database, in: IEEE Conference on Computer Vision and Pattern Recognition, 2009.
- 690 [55] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, et al., Pytorch: An imperative style, high-performance deep learning library, in: Neural Information Processing Systems, 2019.
- [56] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition”, in: International Conference on Learning Representations, 695 2015.

- [57] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, B. Guo, Swin transformer: Hierarchical vision transformer using shifted windows, in: IEEE International Conference on Computer Vision, 2021.