A. Operations Used in Policies

We introduce the operations used in MADAO in Table 6. Internally, magnitudes are restricted within $(0, 1)$ range with sigmoid function and rescaled to the appropriate range. For example, we multiply the internal magnitude $\mu_{\texttt{ShearX}}$ for `ShearX` operation by 0.3. As can been seen in Table 6, there are three operations that have no magnitude parameters. Therefore, each policy has $(11+14+14) \times K$ learnable parameters, where 11 corresponds to the number of magnitude parameters, e.g., $\mu_{\texttt{ShearX}}$, the first 14 corresponds to the number of probability parameters, e.g., $p_{\texttt{ShearX}}$, and the second 14 corresponds to operation selection parameters $\boldsymbol{\pi}$. In our experiments, we set $K = 2$, and thus, the total number of learnable parameters is 78. Note that the original implementation of RandAugment does not include `Invert` in the operation set but we perform experiments with RandAugment using the same operation set as we use for our proposed method, that is including `Invert`.

	Operation	Original Magnitude Range
Affine Transformation	`ShearX`	$[0, 0.3]$
	`ShearY`	$[0, 0.3]$
	`TranslateX`	$[0, 0.45]$
	`TranslateY`	$[0, 0.45]$
	`Rotate`	$[0, 30]$
Color Enhancing Operations	`Invert`	—
	`AutoContrast`	—
	`Equalize`	—
	`Solarize`	$[0, 256]$
	`Color`	$[0, 2]$
	`Posterize`	$[0, 4]$
	`Contrast`	$[0, 2]$
	`Brightness`	$[0, 2]$
	`Sharpness`	$[0, 2]$

Table 6. Operations used in the experiments.

B. Experimental Details

We show hyperparameters of MADAO and Faster AutoAugment in Table 7 and Table 8, respectively. We describe the training details for each dataset in the following.

B.1. CIFAR-10, CIFAR-100 and SVHN

On CIFAR-10 and CIFAR-100, we trained WideResNets for 300 epochs. We used SGD with the initial learning rate of 0.1, the momentum of 0.9 and the weight decay of 5×10^{-4}. The learning rates ware scheduled with cosine annealing with warm restart [35]. On SVHN, we trained WideResNets for 160 epochs. We used SGD with the initial learning rate of 5×10^{-3}, the momentum of 0.9 and the weight decay of 1×10^{-4}. The learning rate is divided by 10 at 80th and 120th epochs. On CIFAR-10, CIFAR-100, and SVHN, we set the batch size to 128.

B.2. ImageNet

On ImageNet, we trained ResNet-50 for 180 epochs with SGD of the base initial learning rate of 0.1, the momentum of 0.9 and the weight decay of 1×10^{-4}. The learning rate is divided by 10 at 60th, 120th and 160th epochs. We set the batch size to 1,024 so that we scale the initial learning rate to 0.4. As the standard data augmentation, we randomly cropped images into 224×224 pixels and randomly flipped horizontally.

B.3. Fine-grained classification

On fine-grained datasets, we trained an ImageNet-pretrained ResNet-18 for 200 epochs and set the batch size to 64. The initial learning rate was set to 0.1, which was scheduled with cosine annealing with warm restart. As the standard data augmentation, we used the same strategy as for ImageNet, including random cropping into 224×224 pixels.

Name	Description	Shared Value
Number of inner steps	s corresponds to `num_inner_iters` in Algorithm 1	60
Warm-up epochs	Initial wth epochs that policy is not updated	30
Temperature	τ for operation selection	1.0

Table 7. Hyperparameters of MADAO.

Description	Value
Training set size for policy training on CIFARs	4,000
Training set size for policy training on SVHN	1,000
Training set size for policy training on ImageNet	6,000
Training set size for policy training on finegrained datasets	1,000
Number of sub-policies on CIFARs, SVHN, and finegrained datasets	1
Number of sub-policies on ImageNet	10

Table 8. Hyperparameters of Faster AutoAugment. For other hyperparameters, we used the ones identical to [17].