

Supplementary Material for: TorMentor: Deterministic dynamic-path, data augmentations with fractals

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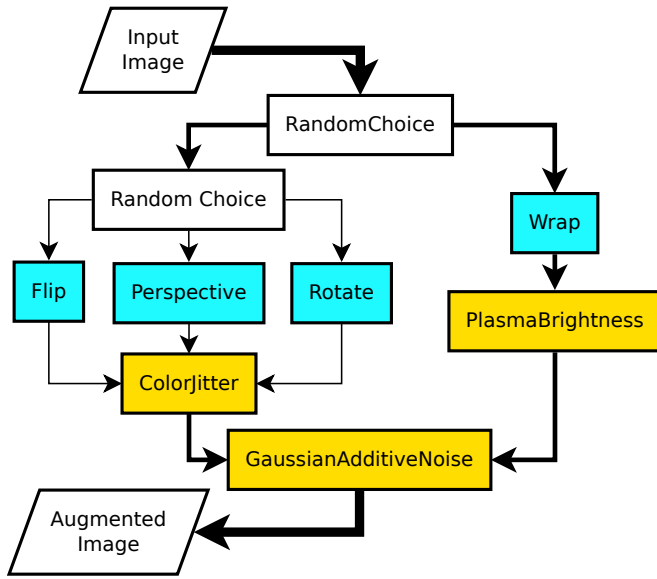


Figure 1. The flow network that is defined in listing 1 ventral operations are shown as cyan, dorsal as yellow, and meta augmentations as white. Notice the arrow thickness represents the probability an augmentation instance passes through the specific path.

1. Supplementary

1.1. Meta Augmentations

The most straightforward way of defining a custom augmentation regiment is through meta-augmentations. In Listing 1 we can see how someone with domain knowledge could express the process generating plausible distortions as an augmentation regiment. In Fig. 1, we can see the flow network that listing 1 produced. Finally, in Fig. 2 we can see an application of 24 augmentation instances from the defined regiment.

```
1 from tormentor import RandomColorJitter,
  RandomFlip, RandomWrap,
  RandomPlasmaBrightness, RandomPerspective,
  RandomGaussianAdditiveNoise, RandomRotate
2
3 linear_aug = (RandomFlip ^ RandomPerspective ^
  RandomRotate) | RandomColorJitter
```

```
4 nonlinear_aug = RandomWrap |
  RandomPlasmaBrightness
5 final_augmentation = (linear_aug ^ nonlinear_aug)
  | RandomGaussianAdditiveNoise
6
7 epochs, batch_size, n_points, width, height = 10,
  5, 20, 320, 240
8
9 for _ in range(epochs):
10     image_batch = torch.rand(batch_size, 3,
11     height, width)
12     segmentation_batch = torch.rand(batch_size,
13     1, height, width).round()
14     augmentation = final_augmentation()
15     augmented_images = augmentation(image_batch)
16     augmented_gt = augmentation(
17     segmentation_batch)
18     # Train and do other things.
```

Listing 1. Meta-augmentations used to define augmentation routing

1.2. Defining a New Augmentation

TorMentor can be customized by writing custom augmentation operations. An augmentation operation must be defined as a Python class. Although augmentations can deal both with samples (3D tensors) The class must implement the method *generate_batch_state* which takes as a parameter the input data in order to know its size. If it is a dorsal operation, it should be inheriting class *ColorAugmentation* and implement the functional method *functional_image* which takes as parameters a batch of data followed by zero to many tensors whose first dimension must be batch size. If on the other hand it is a ventral operation, the functional method must be applied on a sampling field pointing on the image pixels. Regardless of the image size, the sampling field has values between -1 and 1 both horizontally and vertically. In listing 2 the definition of a ventral augmentation mimicking a lens effect can be seen, while in Fig. 3 we can see the defined augmentation applied on a sample of the COCO dataset.

```
1 import tormentor
2
3 class Lens(tormentor.SpatialImageAugmentation):
4     center_x = tormentor.Uniform((-0.3, 0.3))
```

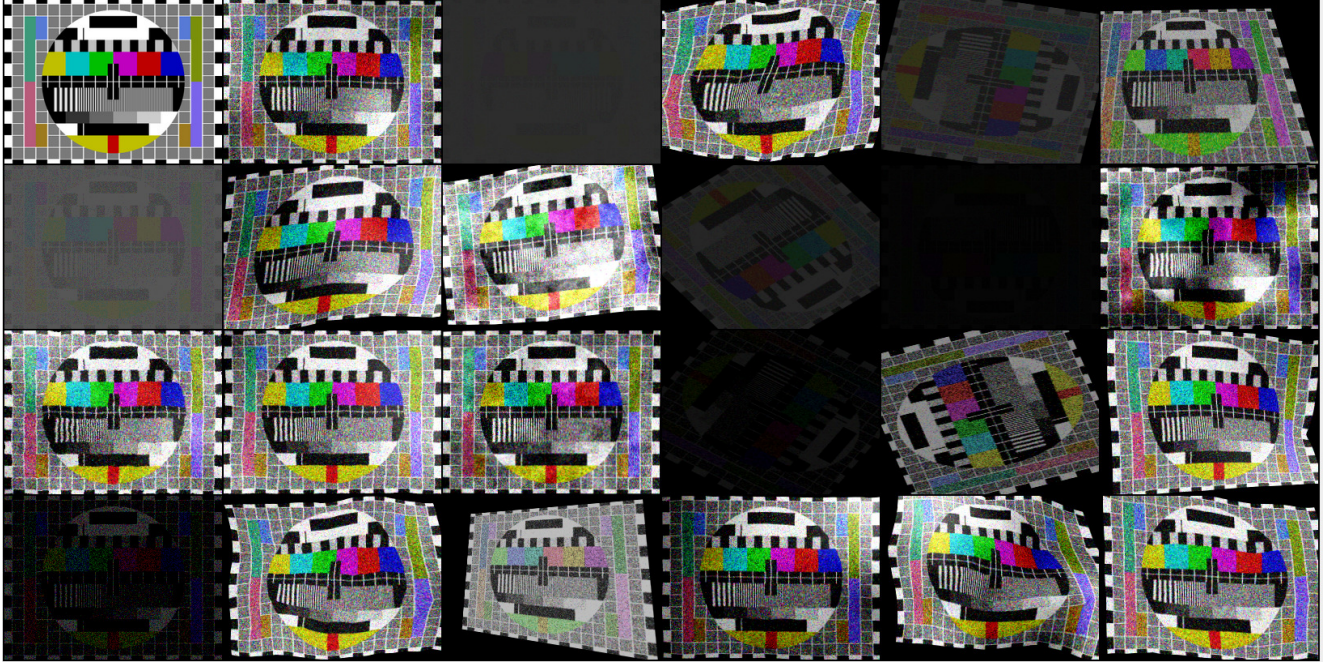


Figure 2. Application of 24 different augmentation instances from the augmentation regiment defined in listing 1 and described in Fig. 1

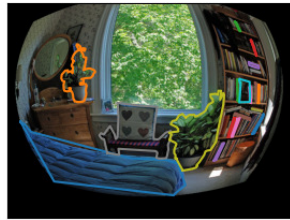


Figure 3. Custom lens augmentation applied on MS-COCO segmentation.

```

20     gamma = gamma.unsqueeze(dim=1).unsqueeze(
21         dim=1)
22     distance = ((center_x - field_x)**2 + (
23         center_y - field_y)**2) ** .5
24     field_x, field_y = (field_x + field_x *
25         distance ** gamma) , (field_y + field_y *
26         distance ** gamma)
27     return field_x, field_y

```

Listing 2. Custom augmentation definition of a lens effect

Notice that the pointcloud domain works perfectly well with polygon defined segmentations.

```

5     center_y = torch.tensor.Uniform((-0.3, 0.3))
6     gamma = torch.tensor.Uniform((1., 1.))
7
8     def generate_batch_state(self, samples):
9         batch_sz = sampling_tensors[0].size(0)
10        gamma = type(self).gamma(batch_sz, device
11        =samples[0].device).view(-1)
12        center_x = type(self).center_x(batch_sz,
13        device=samples[0].device).view(-1)
14        center_y = type(self).center_y(batch_sz,
15        device=samples[0].device).view(-1)
16        return center_x, center_y, gamma
17
18    @classmethod
19    def functional_sampling_field(cls,
20        sampling_field, center_x, center_y, gamma):
21        field_x, field_y = sampling_field
22        center_x = center_x.unsqueeze(dim=1).
23        unsqueeze(dim=1)
24        center_y = center_y.unsqueeze(dim=1).
25        unsqueeze(dim=1)

```