Computer Vision
Term Project Presentation

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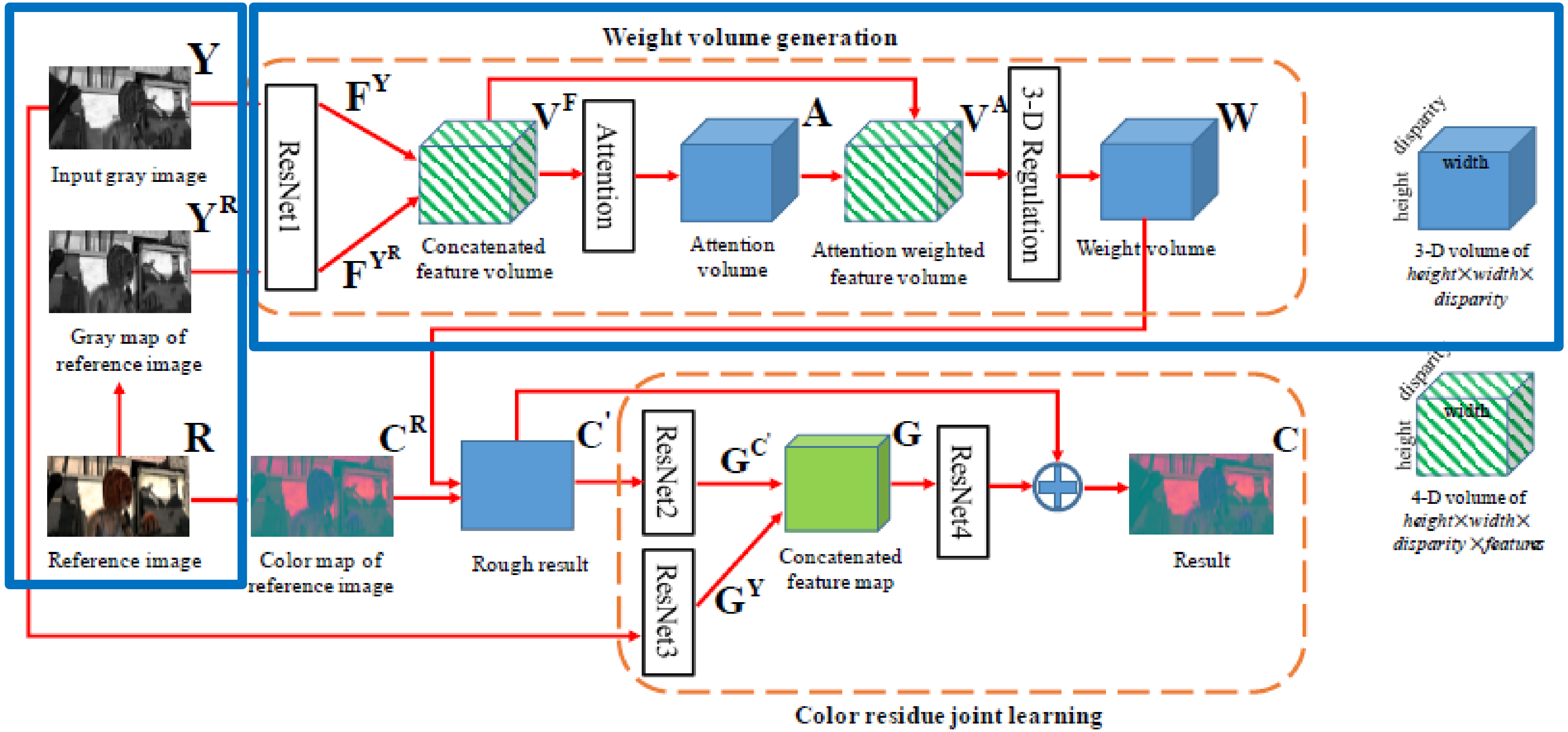
Contents

Introduction

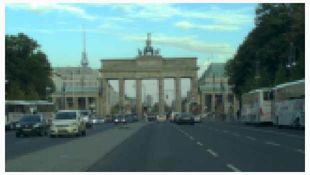
- **Learning a Deep Convolutional Network for Colorization in Monochrome-Color Dual-Lens System**(Xuan Dong et, al. Association for the Advancement of Artificial Intelligence 2019)



Data

- **./dataset.py**
- **Cityscapes** dataset for training
- **Left images** for **Input gray images** and **ground truth**
- **Right images** for **gray map** of reference images
- Add **Gaussian noises**

noise std.	color camera	monochrome camera
Setup1	$0.03\sqrt{\kappa}$	$0.01\sqrt{\kappa}$
Setup2	$0.07\sqrt{\kappa}$	$0.01\sqrt{\kappa}$



leftImg8bit_trainextra.zip (44GB) [md5]

left 8-bit images - trainextra set (19998 images, note that the image "troisdorf_000000_000073_leftImg8bit.png" is corrupt/black)

rightImg8bit_trainextra.zip (44GB) [md5]

right 8-bit images - trainextra set (19998 images)

Model

- **./models.py**
- Define networks(**ResNet1-4, Attention, 3D-regulation**)
- Implement model structure for **Weight volume generation**

```python
class WeightVolGen(nn.Module):
    def __init__(self):
        super(WeightVolGen, self).__init__()
        self.block = ResidualBlock
        # resnet1 for Y(gray image)
        self.resnet1_y = ResNet(8, self.block, 1)
        # resnet1 for YR(ref image)
        self.resnet1_yr = ResNet(8, self.block, 1)
        # attention for Concatenated feature volume
        self.attention = Attention()
        # 3-D Regulation
        self.regulation = Regulation3d(1)

    def forward(self, target_image, guide_image, gt_image):
        feature_map1 = self.resnet1_y(target_image)
        feature_map2 = self.resnet1_y(guide_image)
        attn_weighted_fvol = self.attention(torch.stack([feature_map1, feature_map2], dim=2))
        weight_volume = self.regulation(attn_weighted_fvol)
        return weight_volume
```

Table 1: Summary of our deep colorization architecture. Each 2-D or 3-D convolutional layer represents a block of convolution, batch normalization and ReLu.

	Layer Description	Output Tensor Dim.
	Input gray image $\mathbf{Y}$	$h \times w$
	Gray map of reference Image $\mathbf{Y}^{\mathbf{R}}$	$h \times w$
	ResNet1	
1	5×5 conv, n feat., stride 2	$\frac{h}{2} \times \frac{w}{2} \times n$
2	3×3 conv, n feat.	$\frac{h}{2} \times \frac{w}{2} \times n$
3	3×3 conv, n feat.	$\frac{h}{2} \times \frac{w}{2} \times n$
	add layer 1 and 3 feat. (residue connection)	$\frac{h}{2} \times \frac{w}{2} \times n$
4-17	(repeat layers 2,3 and residual connection)$\times$7	$\frac{h}{2} \times \frac{w}{2} \times n$
18	3×3 conv, n feat., no ReLu/BN	$\frac{h}{2} \times \frac{w}{2} \times n$
	Attention	
19	3-D conv,$1 \times 1 \times 1$,n feat.,Sigmoid,no BN/ReLu	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2} \times n$
20	3-D conv,$1 \times 1 \times 1$,1 feat.,Sigmoid,no BN/ReLu	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2}$
	3-D regulation	
21	3-D conv, $3 \times 3 \times 3$, n feat.	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2} \times n$
22	3-D conv, $3 \times 3 \times 3$, n feat.	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2} \times n$
23	3-D conv, $3 \times 3 \times 3$, $2n$ feat., stride 2	$\frac{h}{4} \times \frac{w}{4} \times \frac{d}{4} \times 2n$
24	3-D conv, $3 \times 3 \times 3$, $2n$ feat.	$\frac{h}{4} \times \frac{w}{4} \times \frac{d}{4} \times 2n$
25	3-D conv, $3 \times 3 \times 3$, $2n$ feat.	$\frac{h}{4} \times \frac{w}{4} \times \frac{d}{4} \times 2n$
26-34	(repeat layer 23, 24, 25)$\times$3	$\frac{h}{32} \times \frac{w}{32} \times \frac{d}{32} \times 2n$
35	$3 \times 3 \times 3$, 3-D trans conv, $2n$ feat., stride 2	$\frac{h}{16} \times \frac{w}{16} \times \frac{d}{16} \times 2n$
	add layer 35 and 31 (residual connection)	$\frac{h}{16} \times \frac{w}{16} \times \frac{d}{16} \times 2n$
36	$3 \times 3 \times 3$, 3-D trans conv, $2n$ feat., stride 2	$\frac{h}{8} \times \frac{w}{8} \times \frac{d}{8} \times 2n$
	add layer 36 and 28 (residual connection)	$\frac{h}{8} \times \frac{w}{8} \times \frac{d}{8} \times 2n$
37	$3 \times 3 \times 3$, 3-D trans conv, $2n$ feat., stride 2	$\frac{h}{4} \times \frac{w}{4} \times \frac{d}{4} \times 2n$
	add layer 37 and 25 (residual connection)	$\frac{h}{4} \times \frac{w}{4} \times \frac{d}{4} \times 2n$
38	$3 \times 3 \times 3$, 3-D trans conv, n feat., stride 2	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2} \times n$
	add layer 38 and 22 (residual connection)	$\frac{h}{2} \times \frac{w}{2} \times \frac{d}{2} \times n$
39	$3 \times 3 \times 3$, 3-D trans conv, 1 feat., no ReLu/BN	$h \times w \times d$
	ResNet2	
40	5×5 conv, n feat.	$h \times w \times n$
41-57	repeat layers 2-18	$h \times w \times n$
	ResNet3	
58-75	repeat layers 40-57	$h \times w \times n$
	ResNet4	
76-92	repeat layers 40-56	$h \times w \times n$
93	3×3 conv, 1 feat. (no ReLu, BN)	$h \times w$

Train

- Implemented with PyTorch
- Model optimizer : RMSProp
- Batch size : 256 x 512 randomly located crop
- Learning late : 0.001
- Loss : Mean Squared Error

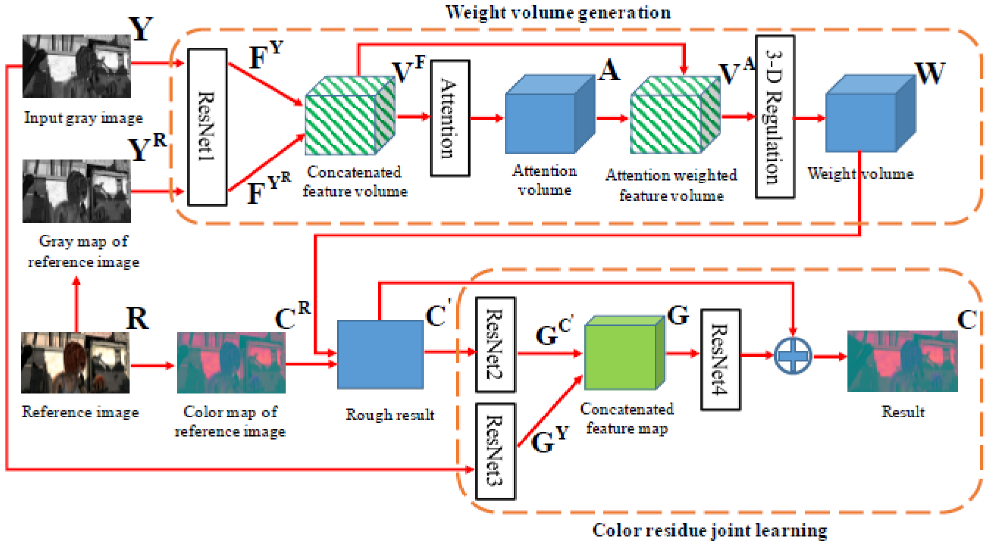
```
criterion = nn.MSELoss()
optimizer = torch.optim.RMSprop(model.parameters(), lr=lr, weight_decay=0, momentum=0)
psnr = PSNR(255.0).to(device)

for epochs in range(epochs):
    train_bar = tqdm(trainloader)

    for train_iter, items in enumerate(train_bar):
        model.train()

        # train 1
        target = Variable(items[0]).to(device)
        guide = Variable(items[1]).to(device)
        gt = Variable(items[2]).to(device)

        output = model(target, guide, gt)
        print('result of Weight volume generation : {}'.format(output.shape))
```



$$C'_{j,i} = \sum_{k=0}^{d-1} W_{j,i,k} C^R_{j,i+k}.$$

Summary

- Stereo datasets preprocessing
- Implement each networks structure
- Define model
- Extract concatenated feature map
- Extract attention volume
- Extract weight volume
- Rough colorization
- Color residue joint learning

Thank you for your Attention.