Self-Supervised Moncular Depth Estimation using Neural Networks

CS 484 Fall 2023 Final Project

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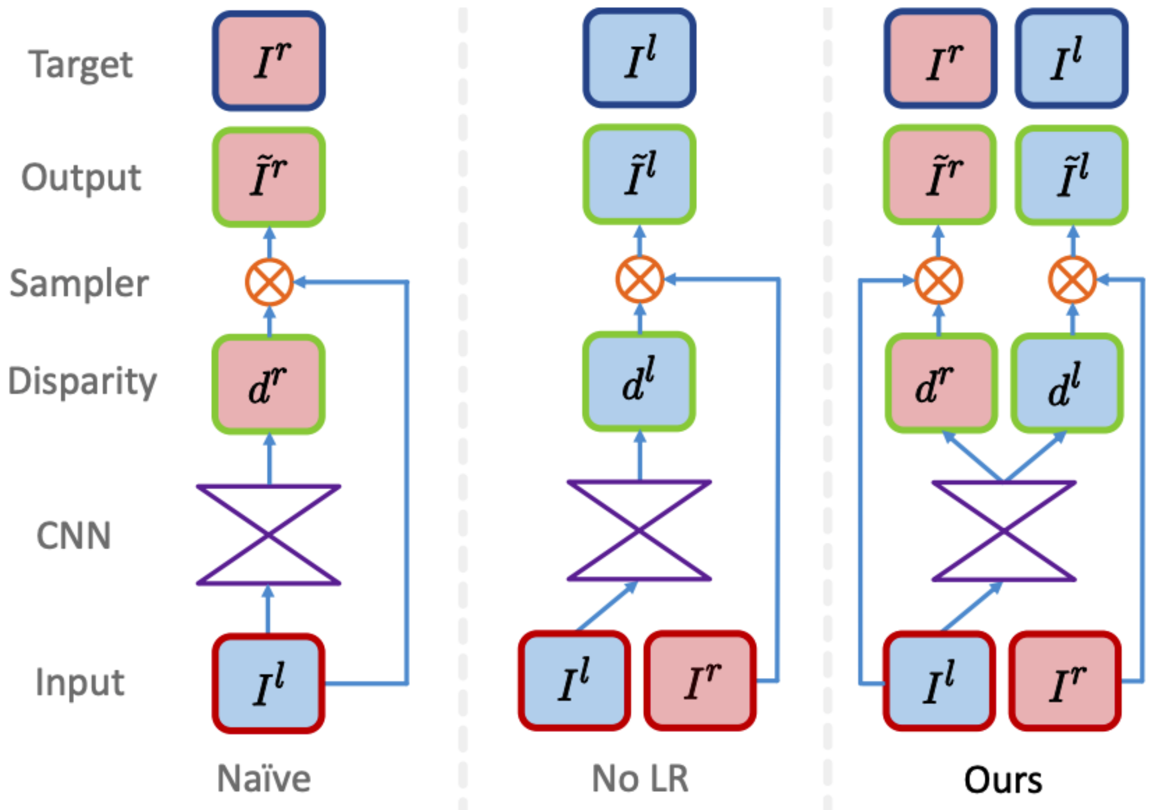
Introduction

Monocular depth estimation is a computer vision task that involves estimating the depth of each pixel given a single 2D (monocular) image. The goal is to derive 3D information from a 2D image.

While many depth-estimation techniques exist like multi-view geometry and stereo reconstruction, machine learning can do better. Learning techniques had been shown to be promising, but most of them utilized fully supervised learning, which relied on having a considerable amount of ground truth depth data at hand.

In 2017, Clément Godard, Oisin Mac Aodha, and Gabriel J. Brostow published a paper titled "Unsupervised Monocular Depth Estimation with Left-Right Consistency" (https://arxiv.org/abs/1609.03677) This paper proposed a new technique for depth estimation which utilized unsupervised or self-supervised learning. It suggests a novel training method (a unique loss function) which allows the CNN to perform depth estimation on a single image, without ground truth data.

This method uses left-right image pairs taken by parallel cameras at a given base-length. It uses the left image to estimate both the left-to-right and right-to-left disparity maps. The left-to-right disparity map is used to reconstruct the right image, and the right-to-left disparity map is used to reconstruct the left image. The reconstructed images are then compared with the original images, and used to drive the loss function.



Imports

In [1]:
```
%matplotlib inline
USE_GPU = False
```

In [2]:
```
# Python Libraries
import random
import math
import numbers
import platform
import copy

# Importing essential libraries for basic image manipulations.
import numpy as np
import PIL
from PIL import Image, ImageOps
import matplotlib.pyplot as plt
from tqdm import tqdm

# We import some of the main PyTorch and TorchVision libraries.
import torch
import torch.nn.functional as F
from torch import nn
from torch.utils.data import DataLoader, ConcatDataset
import torchvision.transforms as transforms
import torchvision.transforms.functional as tF

device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

Dataset

We will be using the KITTI dataset for training our model. Specifically, we will be using left-right image pairs.

The training set consists of:

- 2011_09_29_drive_0071 (1059 image pairs)

The validation set consists of:

- 2011_09_28_drive_0001 (106 image pairs)

The sanity set consists of

- 1 left/right image pair (just to test if things seem to be working)

We will only be using colored images. I have 3 folders in my data folder: train, validate, and sanity. Each folder contains a data folder with two sub-folders called left and right, which contain the image pairs of the same name.

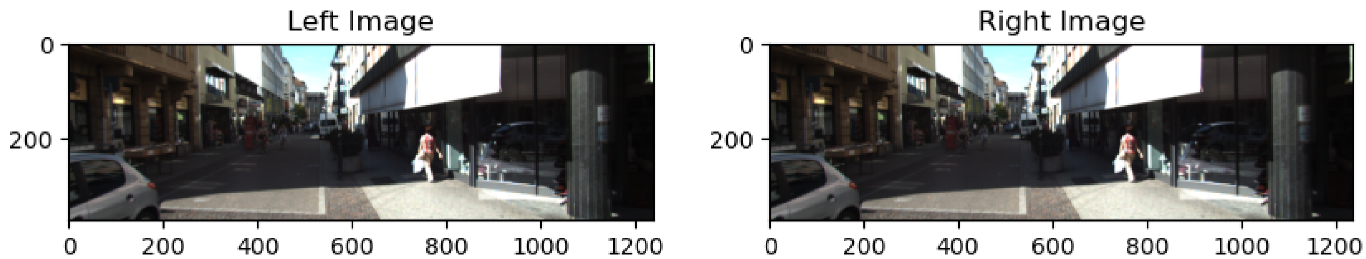
Folder setup:

```
data
|
├── train
|   ├── left
|   |   ├── 0000000000.png
|   |   ├── ...
|   |   └── 0000001059.png
|   └── right
|       ├── 0000000000.png
|       ├── ...
|       └── 0000001059.png
|
├── validate
|   ├── left
|   |   ├── 0000000000.png
|   |   ├── ...
|   |   └── 0000000105.png
|   └── right
|       ├── 0000000000.png
|       ├── ...
|       └── 0000000105.png
|
└── sanity
    ├── left
    |   └── 0000000000.png
    └── right
        └── 0000000000.png
```

In [3]:

```
# Folder Names
train_folder = 'data/train'
validate_folder = 'data/validate'
sanity_folder = 'data/sanity'

# Showing a left and right image pair
left_img_path = 'data/train/left/0000000000.png'
left_img_path = 'data/train/right/0000000000.png'

# Load images
left_img = plt.imread(left_img_path)
right_img = plt.imread(left_img_path)
```

```
# Create a figure and axes
fig, axs = plt.subplots(1, 2, figsize=(10, 5))

# Display left and right images side by side
axs[0].imshow(left_img)
axs[0].set_title('Left Image')

axs[1].imshow(right_img)
axs[1].set_title('Right Image')

plt.show()
```



Transformations

We will apply various transforms to our input images in order to increase the diversity of the data, and allow for a more robust model.

- Resize to 187 x 619 for image consistency
- Randomly flip
- Random brightness
- Random hue
- Random contrast
- Random saturation

In [4]:

```
# Could work on just 1 image (left) or both (left and right)
class JointToTensor(object):
    def __call__(self, target):
        if isinstance(target, list) or isinstance(target, tuple):
            return tF.to_tensor(target[0]), tF.to_tensor(target[1])
        return tF.to_tensor(target)

# Randomly horizontally flip the images
class JointRandomFlip(object):
    def __call__(self, target):
        if random.random() > 0.5: # 50% chance of flipping
            if isinstance(target, list) or isinstance(target, tuple):
                return tF.hflip(target[0]), tF.hflip(target[1])
            return tF.hflip(target)
        return target

# Could work on just 1 image (left) or both (left and right)
# Resize image to make learning easier/more consistent inputs
class JointResize(object):
    def __init__(self, size=(256, 512)):
        self.resize = transforms.Resize(size)

    def __call__(self, target):
        if isinstance(target, list) or isinstance(target, tuple):
            return self.resize(target[0]), self.resize(target[1])
        return self.resize(target)
```

```python
# Adjust brightness randomly
class JointRandomBrightness(object):
    def __init__(self, brightness_factor_range=(0.7, 1.3)):
        self.brightness_factor_range = brightness_factor_range

    def __call__(self, target):
        brightness_factor = random.uniform(*self.brightness_factor_range)
        if isinstance(target, list) or isinstance(target, tuple):
            return (tF.adjust_brightness(target[0], brightness_factor),
                    tF.adjust_brightness(target[1], brightness_factor))
        else:
            return target

# Adjust hue randomly
class JointRandomHue(object):
    def __init__(self, hue_factor_range=(-0.1, 0.1)):
        self.hue_factor_range = hue_factor_range

    def __call__(self, target):
        hue_factor = random.uniform(*self.hue_factor_range)
        if isinstance(target, list) or isinstance(target, tuple):
            return (tF.adjust_hue(target[0], hue_factor),
                    tF.adjust_hue(target[1], hue_factor))
        else:
            return target

# Adjust contrast randomly
class JointRandomContrast(object):
    def __init__(self, contrast_factor_range=(0.7, 1.3)):
        self.contrast_factor_range = contrast_factor_range

    def __call__(self, target):
        contrast_factor = random.uniform(*self.contrast_factor_range)
        if img_right is not None:
            return (tF.adjust_contrast(target[0], contrast_factor),
                    tF.adjust_contrast(target[1], contrast_factor))
        else:
            return target

# Adjust saturation randomly
class JointRandomSaturation(object):
    def __init__(self, saturation_factor_range=(0.7, 1.3)):
        self.saturation_factor_range = saturation_factor_range

    def __call__(self, target):
        saturation_factor = random.uniform(*self.saturation_factor_range)
        if img_right is not None:
            return (tF.adjust_saturation(target[0], saturation_factor),
                    tF.adjust_saturation(target[1], saturation_factor))
        else:
            return target
```

Data Loading

In [5]:

```python
import os
from PIL import Image
from torch.utils.data import Dataset

# Get images
class KITTIDataset(Dataset):
    def __init__(self, root, mode, transform=None):
        self.transform = transform
```

```
        left_dir = os.path.join(root, mode, 'left')
        self.left_images = sorted([os.path.join(left_dir, img)
                for img in os.listdir(left_dir) if img.endswith('.png')])

        right_dir = os.path.join(root, mode, 'right')
        self.right_images = sorted([os.path.join(right_dir, img)
                for img in os.listdir(right_dir) if img.endswith('.png')])

        assert len(self.right_images) == len(self.left_images)

    def __len__(self):
        return len(self.left_images)

    def __getitem__(self, imgNum):
        left_image = Image.open(self.left_images[imgNum])
        right_image = Image.open(self.right_images[imgNum])

        if self.transform:
            return self.transform((left_image, right_image))
        return left_image, right_image
```

In [6]:
```
# Composing transforms for our datasets
training_transform = transforms.Compose([
    JointToTensor(),
    JointResize(),
    JointRandomBrightness(),
    JointRandomContrast(),
    JointRandomHue(),
    JointRandomSaturation(),
    JointRandomFlip(),
])
validation_transform = transforms.Compose([ JointToTensor(), JointResize()
])
sanity_transform = transforms.Compose([ JointToTensor(), JointResize()
])
```

Creating the datasets:

In [7]:
```
train_dataset = KITTIDataset('data', 'train', transform=training_transform)
print("The length of the training set is: ", len(train_dataset))
```

```
The length of the training set is:  1059
```

In [8]:
```
validate_dataset = KITTIDataset('data', 'validate', transform=validation_transform)
print("The length of the validation set is: ", len(validate_dataset))
```

```
The length of the validation set is:  106
```

In [9]:
```
sanity_dataset = KITTIDataset('data', 'sanity', transform=sanity_transform)
print("The length of the sanity set is: ", len(sanity_dataset))
```

```
The length of the sanity set is:  1
```

Creating loaders for the datasets:

In [37]:
```
# Increase TRAIN_BATCH_SIZE if you are using GPU to speed up training.
# When batch size changes, the learning rate may also need to be adjusted.
# Note that batch size maybe limited by your GPU memory, so adjust if you get
# "run out of GPU memory" error.
TRAIN_BATCH_SIZE = 1

VAL_BATCH_SIZE = 1
# If you are NOT using Windows, set NUM_WORKERS to anything you want, e.g. NUM_WORKERS =
```

```
# but Windows has issues with multi-process dataloaders, so NUM_WORKERS must be 0 for Wi
NUM_WORKERS = 0

sanity_loader = DataLoader(sanity_dataset, batch_size=1, num_workers=NUM_WORKERS, shuffl
train_loader = DataLoader(train_dataset, batch_size=TRAIN_BATCH_SIZE, num_workers=NUM_WO
val_loader = DataLoader(validate_dataset, batch_size=VAL_BATCH_SIZE, num_workers=NUM_WOR
```

Model

The depth estimation neural network that the Godard et al paper recommends is as follows:

1. Model architecture

"Encoder"						
layer	**k**	**s**	**chns**	**in**	**out**	**input**
conv1	7	2	3/32	1	2	left
conv1b	7	1	32/32	2	2	conv1
conv2	5	2	32/64	2	4	conv1b
conv2b	5	1	64/64	4	4	conv2
conv3	3	2	64/128	4	8	conv2b
conv3b	3	1	128/128	8	8	conv3
conv4	3	2	128/256	8	16	conv3b
conv4b	3	1	256/256	16	16	conv4
conv5	3	2	256/512	16	32	conv4b
conv5b	3	1	512/512	32	32	conv5
conv6	3	2	512/512	32	64	conv5b
conv6b	3	1	512/512	64	64	conv6
conv7	3	2	512/512	64	128	conv6b
conv7b	3	1	512/512	128	128	conv7

"Decoder"						
layer	**k**	**s**	**chns**	**in**	**out**	**input**
upconv7	3	2	512/512	128	64	conv7b
iconv7	3	1	1024/512	64	64	upconv7+conv6b
upconv6	3	2	512/512	64	32	iconv7
iconv6	3	1	1024/512	32	32	upconv6+conv5b
upconv5	3	2	512/256	32	16	iconv6
iconv5	3	1	512/256	16	16	upconv5+conv4b
upconv4	3	2	256/128	16	8	iconv5
iconv4	3	1	128/128	8	8	upconv4+conv3b
disp4	3	1	128/2	8	8	iconv4
upconv3	3	2	128/64	8	4	iconv4
iconv3	3	1	130/64	4	4	upconv3+conv2b+disp4*
disp3	3	1	64/2	4	4	iconv3
upconv2	3	2	64/32	4	2	iconv3
iconv2	3	1	66/32	2	2	upconv2+conv1b+disp3*
disp2	3	1	32/2	2	2	iconv2
upconv1	3	2	32/16	2	1	iconv2
iconv1	3	1	18/16	1	1	upconv1+disp2*
disp1	3	1	16/2	1	1	iconv1

The encoder consists of several convolutional kernals (cnv1 to cnv7b). We will use Resnet-18.

The decoder uses skip-connections from the encoder's activation blocks, enabling it to resolve higher resolution details. The decoder also outputs disparity predictions at four different scales (disp4 to disp1), which double in resolution at each level.

The network predicts two disparity maps at each output scale: left-to-right and right-to-left.

Helper methods for the decoder:

In [11]:
```
class iconv(nn.Module):
    def __init__(self, in_layers, out_layers, kernel_size, stride):
        super(iconv, self).__init__()
        padding = int(np.floor((kernel_size-1)/2))

        self.layers = nn.Sequential(
            nn.Conv2d(in_layers, out_layers, kernel_size, stride, padding),
            nn.BatchNorm2d(out_layers),
            nn.ELU(inplace=True),
        )

    def forward(self, x):
        return self.layers(x)
```

```python
class upconv(nn.Module):
    def __init__(self, in_layers, out_layers, kernel_size, scale):
        super(upconv, self).__init__()
        self.scale = scale
        self.layers = iconv(in_layers, out_layers, kernel_size, 1)

    def forward(self, x):
        x = F.interpolate(x, scale_factor=self.scale, mode='bilinear',
                          align_corners=True)
        return self.layers(x)

class disp(nn.Module):
    def __init__(self, num_in_layers):
        super(disp, self).__init__()
        self.conv = nn.Conv2d(num_in_layers, 2, kernel_size=3, stride=1, padding=1)
        self.normalize = nn.BatchNorm2d(2)
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        x = self.conv(x)
        x = self.normalize(x)
        return 0.3 * self.sigmoid(x)
```

Implementing the Network (Encoder and Decoder Layers)

In [12]:

```python
import torchvision.models as models

class MyNet(nn.Module):
    def __init__(self, criterion=None):
        super(MyNet, self).__init__()

        # Encoding layers
        self.resnet18 = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
        self.criterion = criterion # Loss function

        ds5 = nn.Sequential(
                    nn.Conv2d(512, 512, kernel_size=(1, 1), stride=(2, 2), bias=False),
                    nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
                                   track_running_stats=True),
        )
        # Additional layers for the encoder to follow paper
        self.layer5 = models.resnet.BasicBlock(512, 512, stride=(2, 2), downsample=ds5)
        self.layer6 = models.resnet.BasicBlock(512, 512)

        # Decoding layers
        self.upconv7 = upconv(512, 512, 3, 2)
        self.iconv7 = iconv(512 + 512, 512, 3, 1)

        self.upconv6 = upconv(512, 512, 3, 2)
        self.iconv6 = iconv(256 + 512, 512, 3, 1)

        self.upconv5 = upconv(512, 256, 3, 2)
        self.iconv5 = iconv(128 + 256, 256, 3, 1)

        self.upconv4 = upconv(256, 128, 3, 2)
        self.iconv4 = iconv(64 + 128, 128, 3, 1)
        self.disp4_layer = disp(128)

        self.upconv3 = upconv(128, 64, 3, 1)
        self.iconv3 = iconv(64 + 64 + 2, 64, 3, 1)
        self.disp3_layer = disp(64)

        self.upconv2 = upconv(64, 32, 3, 2)
```

```python
        self.iconv2 = iconv(64 + 32 + 2, 32, 3, 1)
        self.disp2_layer = disp(32)

        self.upconv1 = upconv(32, 16, 3, 2)
        self.iconv1 = iconv(16 + 2, 16, 3, 1)
        self.disp1_layer = disp(16)


    def forward(self, left, right=None):

        # Encoder
        skip1 = self.resnet18.conv1(left)
        s1 = self.resnet18.bn1(skip1)
        s1 = self.resnet18.relu(s1)
        skip2 = self.resnet18.maxpool(s1)
        skip3 = self.resnet18.layer1(skip2)
        skip4 = self.resnet18.layer2(skip3)
        skip5 = self.resnet18.layer3(skip4)
        skip6 = self.resnet18.layer4(skip5)
        skip7 = self.layer5(skip6)
        x = self.layer6(skip7)

        # Decoder
        upconv7 = self.upconv7(x)
        iconv7 = self.iconv7(torch.cat((upconv7, skip6), 1))

        upconv6 = self.upconv6(iconv7)
        iconv6 = self.iconv6(torch.cat((upconv6, skip5), 1))

        upconv5 = self.upconv5(iconv6)
        iconv5 = self.iconv5(torch.cat((upconv5, skip4), 1))

        upconv4 = self.upconv4(iconv5)
        iconv4 = self.iconv4(torch.cat((upconv4, skip3), 1))
        disp4 = self.disp4_layer(iconv4)
        udisp4 = nn.functional.interpolate(disp4, scale_factor=1, mode='bilinear',
                                           align_corners=True)
        disp4 = nn.functional.interpolate(disp4, scale_factor=0.5, mode='bilinear',
                                          align_corners=True)

        upconv3 = self.upconv3(iconv4)
        iconv3 = self.iconv3(torch.cat((upconv3, skip2, udisp4), 1))
        disp3 = self.disp3_layer(iconv3)
        udisp3 = nn.functional.interpolate(disp3, scale_factor=2, mode='bilinear',
                                           align_corners=True)

        upconv2 = self.upconv2(iconv3)
        iconv2 = self.iconv2(torch.cat((upconv2, skip1, udisp3), 1))
        disp2 = self.disp2_layer(iconv2)
        udisp2 = nn.functional.interpolate(disp2, scale_factor=2, mode='bilinear',
                                           align_corners=True)

        upconv1 = self.upconv1(iconv2)
        iconv1 = self.iconv1(torch.cat((upconv1, udisp2), 1))
        disp1 = self.disp1_layer(iconv1)

        if self.training:
            # Return the loss if in training mode
            return self.criterion([disp1, disp2, disp3, disp4], [left, right])
        else:
            # Return the actual prediction otherwise
            return disp1
```

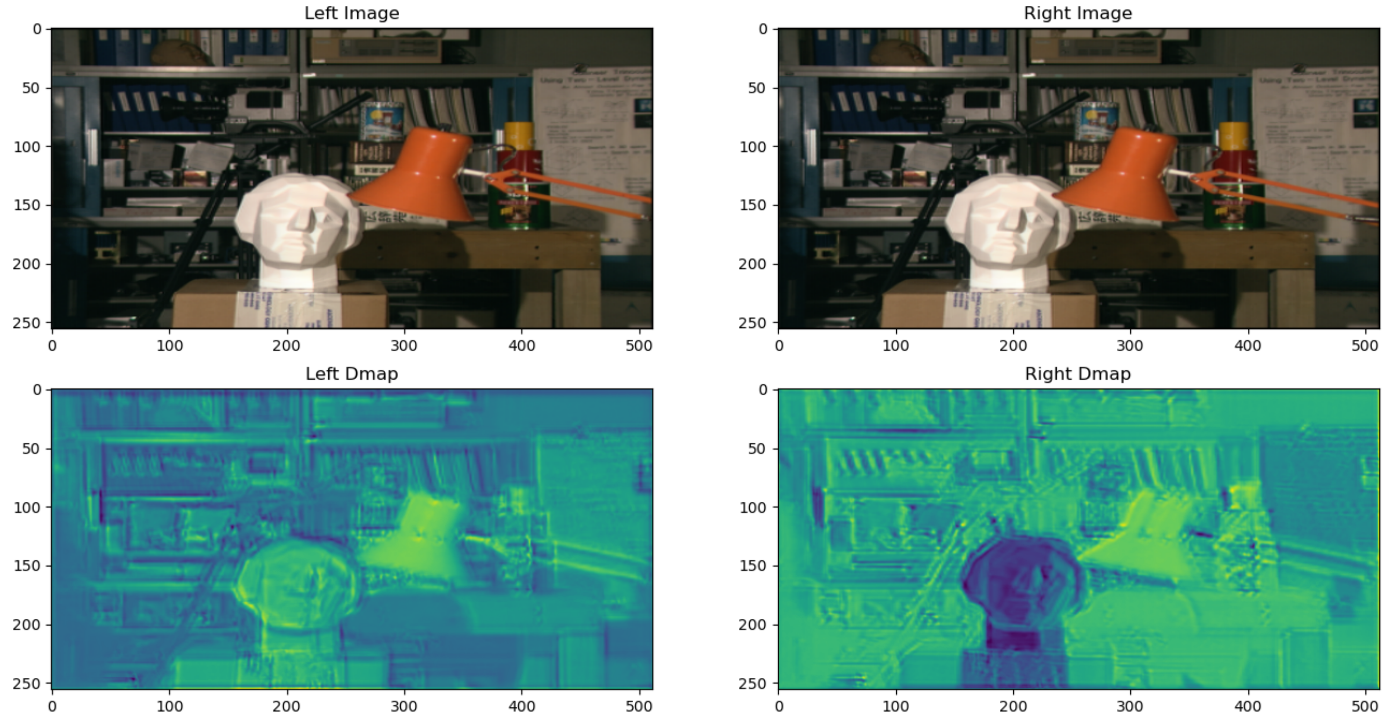
Testing Untrained Network on a Sample

We will plot the original left and right image, and then their disparity maps that the untrained neural network gives us.

In [13]:
```
def display_disparity(net, dataset, i, disp_show=True):
    net.eval()
    sample = dataset[i]
    dmap = net.forward(sample[0][None].to(device)).to('cpu').detach()

    dmapL = dmap[:,0,:,:].unsqueeze(1)
    dmapR = dmap[:,1,:,:].unsqueeze(1)

    if disp_show:
        fig = plt.figure(figsize=(16,8))
        ax = fig.add_subplot(2,2,1)
        plt.title('Left Image')
        ax.imshow(sample[0].permute(1, 2, 0))
        ax = fig.add_subplot(2,2,2)
        plt.title('Right Image')
        ax.imshow(sample[1].permute(1, 2, 0))
        ax = fig.add_subplot(2,2,3)
        plt.title('Left Dmap')
        ax.imshow(dmapL[0][0])
        ax = fig.add_subplot(2,2,4)
        plt.title('Right Dmap')
        ax.imshow(dmapR[0][0])

    return dmap
```

In [14]:
```
# Test the untrained network on some sample images
untrained_net = MyNet().eval().to(device)
dmap = display_disparity(untrained_net, sanity_dataset, 0)
```

```
/Users/nimunbajwa/anaconda3/lib/python3.11/site-packages/torchvision/transforms/function
al.py:1603: UserWarning: The default value of the antialias parameter of all the resizin
g transforms (Resize(), RandomResizedCrop(), etc.) will change from None to True in v0.1
7, in order to be consistent across the PIL and Tensor backends. To suppress this warnin
g, directly pass antialias=True (recommended, future default), antialias=None (current d
efault, which means False for Tensors and True for PIL), or antialias=False (only works
on Tensors - PIL will still use antialiasing). This also applies if you are using the in
ference transforms from the models weights: update the call to weights.transforms(antial
ias=True).
  warnings.warn(
```



It looks like we're getting our disparity maps from the untrained neural network. Let's define our loss function now.

Loss

The loss function that is proposed by the paper consists of 3 components:

- Appearance Matching Loss C_{ap}: How similar is the reconstructed image to the original image. This loss uses the L1 norm and Structural Similarity Index measure (SSIM) for the comparison.

$$C_{ap} = \frac{1}{N} \sum_{ij} \alpha \frac{1 - SSIM(I_{ij}\tilde{I_{ij}})}{2} + (1 - \alpha)\|I_{ij} - \tilde{I_{ij}}\|$$

- Disparity Smoothness Loss C_{ds}: Encouraging smoothness in disparities. This loss uses an L1 penalty on the disparity gradients.

$$C_{ds} = \frac{1}{N} \sum_{ij} |\partial_x d_{ij}| e^{-\|\partial_x I_{ij}\|} + |\partial_y d_{ij}| e^{-\|\partial_y I_{ij}\|}$$

- Left-Right Disparity Consistency Loss C_{lr}: Encouraging consistency between left and right image disparities. This loss uses an L1 left-right disparity consistency penalty.

$$C_{lr} = \frac{1}{N} \sum_{ij} |d^l_{ij} - d^r_{ij+d^l_{ij}}|$$

These losses are defined for left and right images.

The total monocular depth loss is:

$$C_s = \alpha_{ap}(C^l_a p + C^r_a p) + \alpha_{ds}(C^l_d s + C^r_d s) + \alpha_{lr}(C^l_l r + C^r_l r)$$

Where Here, $\alpha_{ap} = 1, \alpha_{ds} = \frac{1}{r}, \alpha_{lr} = 1$ are the weights assigned to each type of loss.

Image Generation

One major concept in this paper is how the right image is recreated using the left image and the left-right disparity map. We will be implementing the method that does this below:

In [15]:
```
def generate_image(img_L, LtoRdmap):
    """
    args:
        img_L: tensor of size [batch_size, channels, height, width]
        LtoRdmap: tensor of size [batch_size, channels, height, width]

        Return:
            (tensor): generated img_R using img_L and disparity map
    """

    batch_size, channels, height, width = img_L.shape
    LtoRdmap = LtoRdmap[:, 0, :, :].to(device)

    # Normalize pixel positions to [0, 1]
    a = torch.linspace(0, 1, height)
    b = torch.linspace(0, 1, width)
    meshy, meshx = torch.meshgrid(a, b)
    meshx = meshx.repeat(batch_size, 1, 1).to(device)
    meshy = meshy.repeat(batch_size, 1, 1).to(device)

    flowfield = torch.stack((meshx + LtoRdmap, meshy), dim=3).type_as(img_L)
    return F.grid_sample(img_L, 2 * flowfield - 1, mode='bilinear', padding_mode='zeros'
```

Appearance Matching Loss

How similar is the reconstructed image to the original image.

$$C_{ap} = \frac{1}{N} \sum_{ij} \alpha \frac{1 - SSIM(I_{ij} \tilde{I_{ij}})}{2} + (1 - \alpha) \| I_{ij} - \tilde{I_{ij}} \|$$

In [16]:
```
class appearanceMatchingLoss(nn.modules.Module):
    """
        Compares the reconstructed image with the original image
        Args:
            dmap: disparity map
            img: input image (reconstructed)
            alpha: float from 0-1 (used in SSIM)
        Return:
            (float): appearance matching loss
        """
    def __init__(self, alpha = 0.85):
        super(appearanceMatchingLoss, self).__init__()
        self.alpha = alpha

    # SSIM implementation from
        # https://github.com/mrharicot/monodepth/blob/master/monodepth_model.py#L91
    def SSIM(self, x, y):
        C1 = 0.01 ** 2
        C2 = 0.03 ** 2

        mu_x = nn.AvgPool2d(3, 1)(x)
        mu_y = nn.AvgPool2d(3, 1)(y)
        mu_x_mu_y = mu_x * mu_y
        mu_x_sq = mu_x.pow(2)
```

```
        mu_y_sq = mu_y.pow(2)

        sigma_x = nn.AvgPool2d(3, 1)(x * x) - mu_x_sq
        sigma_y = nn.AvgPool2d(3, 1)(y * y) - mu_y_sq
        sigma_xy = nn.AvgPool2d(3, 1)(x * y) - mu_x_mu_y

        SSIM_n = (2 * mu_x_mu_y + C1) * (2 * sigma_xy + C2)
        SSIM_d = (mu_x_sq + mu_y_sq + C1) * (sigma_x + sigma_y + C2)
        SSIM = SSIM_n / SSIM_d

        return torch.clamp((1 - SSIM) / 2, 0, 1)

    def forward(self, x, y):
        ssim = self.SSIM(x, y)
        ssim_loss = self.alpha * torch.mean(ssim)
        mae = (1 - self.alpha) * torch.mean(torch.abs(x - y))
        return ssim_loss + mae
```

Disparity Smoothness Loss

Encouraging smoothness in disparities.

$$C_{ds} = \frac{1}{N} \sum_{ij} |\partial_x d_{ij}| e^{-\|\partial_x I_{ij}\|} + |\partial_y d_{ij}| e^{-\|\partial_y I_{ij}\|}$$

In [17]:
```
class disparitySmoothnessLoss(nn.modules.Module):
    """
        Encourages smoothness, penalizes discontinuities
        in disparities
        Args:
            dmap: disparity map
            img: input image
        Return:
            (float): disparity smoothness loss
        """
    def __init__(self):
        super(disparitySmoothnessLoss, self).__init__()

    # Calculating gradients
    def gradientX(self, img):
        img = F.pad(img, (0, 1, 0, 0), mode="replicate")
        return img[:, :, :, :-1] - img[:, :, :, 1:]
    def gradientY(self, img):
        img = F.pad(img, (0, 0, 0, 1), mode="replicate")
        return img[:, :, :-1, :] - img[:, :, 1:, :]

    def forward(self, dmap, img):
        dmapDX = torch.abs(self.gradientX(dmap))
        dmapDY = torch.abs(self.gradientY(dmap))
        imgDX = torch.abs(self.gradientX(img))
        imgDY = torch.abs(self.gradientY(img))

        dslDX = dmapDX * torch.exp(-torch.mean(imgDX, 1, keepdim=True))
        dslDY = dmapDY * torch.exp(-torch.mean(imgDY, 1, keepdim=True))
        return torch.mean(dslDX + dslDY)
```

Left-Right Disparity Consistency Loss

Encouraging consistency between left and right image disparities.

$$C_{lr} = \frac{1}{N}\sum_{ij} |d^l_{ij} - d^r_{ij+d^l_{ij}}|$$

In [18]:
```
class leftRightConsistencyLoss(nn.modules.Module):
    """
        Args:
            dmapL: left disparity map
            dmapR: right disparity map
        Return:
            (float): left-right consistency loss
    """
    def __init__(self):
        super(leftRightConsistencyLoss, self).__init__()

    def forward(self, dmapL, dmapR):
        dmapProjR = generate_image(dmapR, -dmapL)
        dmapProjL = generate_image(dmapL, dmapR)
        mProjR = torch.mean(torch.abs(dmapProjR  - dmapL))
        mProjL = torch.mean(torch.abs(dmapProjL  - dmapR))
        return mProjL + mProjR
```

Overall Monocular Depth Loss

The total monocular depth loss is:

$$C_s = \alpha_{ap}(C^l_a p + C^r_a p) + \alpha_{ds}(C^l_d s + C^r_d s) + \alpha_{lr}(C^l_l r + C^r_l r)$$

Where Here, $\alpha_{ap} = 1, \alpha_{ds} = \frac{1}{r}, \alpha_{lr} = 1$ are the weights assigned to each type of loss.

In [19]:
```
def scale(img):
    """
        Scales the images by a factor of 1, 0.5, 0.25, and 0.125.
        Args:
            img: input image
        Return:
            (list): list of images that are scaled
    """
    images = []
    _, _, h, w = img.size()

    for scale in [1, 0.5, 0.25, 0.125]:
        newSize = (int(h * s), int(w * s))
        scaledImg = F.interpolate(img, size=newSize, mode='bilinear',
                                  align_corners=True)
        images.append(scaledImg)
    return images
```

In [20]:
```
class monocularDepthLoss(nn.modules.Module):
    def __init__(self, device='cpu', alpha_ap = 1, alpha_ds = 1, alpha_lr = 1):
        super(monocularDepthLoss, self).__init__()
        self.alpha_ap = alpha_ap
        self.alpha_ds = alpha_ds
        self.alpha_lr = alpha_lr
        self.C_ap = appearanceMatchingLoss().to(device)
        self.C_ds = disparitySmoothnessLoss().to(device)
        self.C_lr = leftRightConsistencyLoss().to(device)

    def scale(self, img):
        """
            Scales the images by a factor of 1, 0.5, 0.25, and 0.125.
```

```
        Args:
            img: input image
        Return:
            (list): list of images that are scaled
    """
    images = []
    _, _, h, w = img.size()

    for scale in [1, 0.5, 0.25, 0.125]:
        newSize = (int(h * scale), int(w * scale))
        scaledImg = F.interpolate(img, size=newSize, mode='bilinear',
                                  align_corners=True)
        images.append(scaledImg)
    return images

def __call__(self, input, target):
    """
    Args:
        input [disp1, disp2, disp3, disp4]
        target [left, right]
    Return:
        (float): monocular depth loss
    """
    imgL, imgR = target
    imgL_scaled = self.scale(imgL)
    imgR_scaled = self.scale(imgR)

    dmapL = [dmap[:, 0, :, :].unsqueeze(1) for dmap in input]
    dmapR = [dmap[:, 1, :, :].unsqueeze(1) for dmap in input]

    # Shift left when using the left dmap
    imgL_reconstructed = [generate_image(im, -dmap)
                          for im, dmap in zip(imgR_scaled, dmapL)]
    imgR_reconstructed = [generate_image(im, dmap)
                          for im, dmap in zip(imgL_scaled, dmapR)]

    # Appearance matching loss
    apLoss_L = [self.C_ap(input, target)
                for input, target in zip(imgL_reconstructed, imgL_scaled)]
    apLoss_R = [self.C_ap(input, target)
                for input, target in zip(imgR_reconstructed, imgR_scaled)]

    self.lossAP = self.alpha_ap * sum(apLoss_L + apLoss_R)

    # Disparity Smoothness loss
    dsLoss_L = [self.C_ds(dmapL[i], dmapR[i]) / 2 ** i for i in range(4)]
    dsLoss_R = [self.C_ds(dmapR[i], dmapL[i]) / 2 ** i for i in range(4)]

    self.lossDS = self.alpha_ds * sum(dsLoss_L + dsLoss_R)

    # Left Right Consistency Loss
    self.lossLR = self.alpha_lr * sum([self.C_lr(L, R) for L, R in zip(dmapL, dmapR)

    return self.lossAP + self.lossDS + self.lossLR
```

Disparity Sample

We will use the sample displarity maps and images below to test our loss functions.

In [21]:

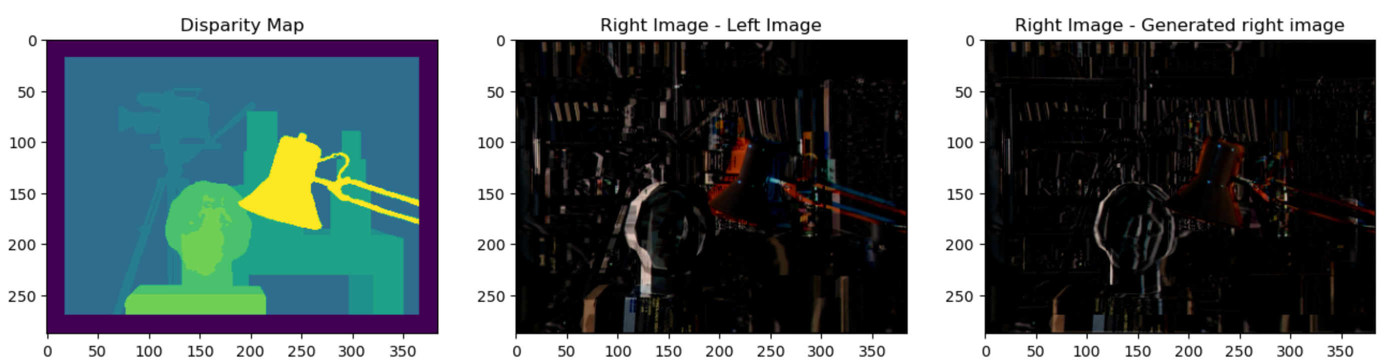
```
import matplotlib.image as image

# Retrieving Images
img_left = tF.to_tensor(image.imread("images/scene1.row3.col3.ppm"))
```

```
img_right = tF.to_tensor(image.imread("images/scene1.row3.col4.ppm"))
img_gt = torch.from_numpy(image.imread("images/truedisp.row3.col3.pgm") / 16)
img_gt = img_gt / img_gt.shape[0]

generatedImgR = generate_image(img_left[None], img_gt[None, None])

# Displaying images
fig = plt.figure(figsize=(16,8))
ax = fig.add_subplot(1,3,1)
plt.title('Disparity Map')
ax.imshow(img_gt)

ax = fig.add_subplot(1,3,2)
plt.title('Right Image - Left Image')
ax.imshow((img_right - img_left).permute(1, 2, 0))

ax = fig.add_subplot(1,3,3)
plt.title('Right Image - Generated right image')
ax.imshow(img_right.permute(1, 2, 0) - generatedImgR[0].permute(1, 2, 0))
```

```
/Users/nimunbajwa/anaconda3/lib/python3.11/site-packages/torchvision/transforms/function
al.py:152: UserWarning: The given NumPy array is not writable, and PyTorch does not supp
ort non-writable tensors. This means writing to this tensor will result in undefined beh
avior. You may want to copy the array to protect its data or make it writable before con
verting it to a tensor. This type of warning will be suppressed for the rest of this pro
gram. (Triggered internally at /Users/runner/work/pytorch/pytorch/pytorch/torch/csrc/uti
ls/tensor_numpy.cpp:212.)
  img = torch.from_numpy(pic.transpose((2, 0, 1))).contiguous()
/Users/nimunbajwa/anaconda3/lib/python3.11/site-packages/torch/functional.py:504: UserWa
rning: torch.meshgrid: in an upcoming release, it will be required to pass the indexing
argument. (Triggered internally at /Users/runner/work/pytorch/pytorch/pytorch/aten/src/A
Ten/native/TensorShape.cpp:3527.)
  return _VF.meshgrid(tensors, **kwargs)  # type: ignore[attr-defined]
/Users/nimunbajwa/anaconda3/lib/python3.11/site-packages/torch/nn/functional.py:4296: Us
erWarning: Default grid_sample and affine_grid behavior has changed to align_corners=Fal
se since 1.3.0. Please specify align_corners=True if the old behavior is desired. See th
e documentation of grid_sample for details.
  warnings.warn(
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
[0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
[0..255] for integers).
```

Out[21]:

```
<matplotlib.image.AxesImage at 0x14933edd0>
```



Testing Appearance Matching Loss Calculation

In [22]:

```
print(appearanceMatchingLoss()(img_right[None], generatedImgR))
```

```
tensor(0.1623)
```

Testing Disparity Smoothness Loss Calculation

In [23]:
```
print(disparitySmoothnessLoss()(img_gt[None, None], img_left[None]))
print(disparitySmoothnessLoss()(img_left[None], img_gt[None, None]))
```

```
tensor(0.0006, dtype=torch.float64)
tensor(0.0545, dtype=torch.float64)
```

Testing Left-Right Disparity Consistency Loss Calculation

In [27]:
```
print(leftRightConsistencyLoss()(img_gt[None, None], img_gt[None, None]))
```

```
tensor(0.0042, dtype=torch.float64)
```

Testing Overall Monocular Depth Loss Calculation

In [28]:
```
test = [torch.stack((dmap[:,0], dmap[:,0]), dim=1)
        for dmap in monocularDepthLoss().scale(img_gt[None, None])]
print("Test Image Shape: ", test[0].shape)
print("Test Prediction: ", monocularDepthLoss()(test, [img_left[None], img_right[None]]))
```

```
Test Image Shape:  torch.Size([1, 2, 288, 384])
Test Prediction:  tensor(1.3256, dtype=torch.float64)
```

Training

Training Loop

Here we will define the training loop for the ML model.

In [38]:
```
def train(train_loader, net, optimizer, loss_graph):
    net.train()
    for i, data in enumerate(train_loader):
        left = data[0].to(device)
        right = data[1].to(device)

        optimizer.zero_grad()
        main_loss = net(left=left, right=right)
        loss_graph.append(main_loss.item()) # Populate this list to graph the loss
        main_loss.backward()
        optimizer.step()

    return main_loss
```

Overfitting the network: Training on a single image pair

From A5: Single image training is helpful for debugging and hyper-parameter tuning (e.g. learning rate, etc.) as it is fast even on a single CPU. In particular, you can work with a single image until your loss function is consistently decreasing during training loop and the network starts producing a reasonable output for this training image. Training on a single image also teaches about overfitting, particualrly when comparing it with more thorough forms of network training.

We will operate on our sanity dataset.

In [42]:
```
%%time
%matplotlib notebook
%matplotlib inline
```

```python
sanity_net = MyNet().to(device)

# set loss function for the net
sanity_net.criterion = monocularDepthLoss(device).to(device)

loader = sanity_loader
optimizer = torch.optim.Adam(sanity_net.parameters(), lr=0.01)

EPOCH = 300

# switch to train mode
sanity_net.train()

print("Starting Training...")

loss_graph = []

fig = plt.figure(figsize=(12,6))
plt.subplots_adjust(bottom=0.2,right=0.85,top=0.5)
ax = fig.add_subplot(1,1,1)

for e in range(EPOCH):
    loss = train(loader, sanity_net, optimizer, loss_graph)
    ax.clear()
    ax.set_xlabel('iterations')
    ax.set_ylabel('loss value')
    ax.set_title('Training loss curve for SANITY_NET')
    ax.plot(loss_graph, label='training loss')
    ax.legend(loc='upper right')
    fig.canvas.draw()
    print("Epoch: {} Loss: {}".format(e, loss))
```

```
Starting Training...
Epoch: 0 Loss: 3.6375668048858643
Epoch: 1 Loss: 3.418206214904785
Epoch: 2 Loss: 3.2668352127075195
Epoch: 3 Loss: 3.185068130493164
Epoch: 4 Loss: 3.158088207244873
Epoch: 5 Loss: 3.0712218284606934
Epoch: 6 Loss: 3.043506622314453
Epoch: 7 Loss: 2.9944636821746826
Epoch: 8 Loss: 2.96956729888916
Epoch: 9 Loss: 2.9461679458618164
Epoch: 10 Loss: 2.9035425186157227
Epoch: 11 Loss: 2.8825979232788086
Epoch: 12 Loss: 2.8767805099487305
Epoch: 13 Loss: 2.8470005989074707
Epoch: 14 Loss: 2.8290233612060547
Epoch: 15 Loss: 2.806981325149536
Epoch: 16 Loss: 2.7829670906066895
Epoch: 17 Loss: 2.7670891284942627
Epoch: 18 Loss: 2.7474145889282227
Epoch: 19 Loss: 2.7258591651916504
Epoch: 20 Loss: 2.7132880687713623
Epoch: 21 Loss: 2.7008438110351562
Epoch: 22 Loss: 2.687986373901367
Epoch: 23 Loss: 2.6738545894622803
Epoch: 24 Loss: 2.6552116870880127
Epoch: 25 Loss: 2.6439342498779297
Epoch: 26 Loss: 2.6408944129943848
Epoch: 27 Loss: 2.63472843170166
Epoch: 28 Loss: 2.614704132080078
Epoch: 29 Loss: 2.6133244037628174
Epoch: 30 Loss: 2.5962791442871094
Epoch: 31 Loss: 2.577425241470337
Epoch: 32 Loss: 2.57458233833313
```

```
Epoch: 33 Loss: 2.549396514892578
Epoch: 34 Loss: 2.5354950428009033
Epoch: 35 Loss: 2.5174221992492676
Epoch: 36 Loss: 2.5059289932250977
Epoch: 37 Loss: 2.4998323917388916
Epoch: 38 Loss: 2.4950265884399414
Epoch: 39 Loss: 2.4766149520874023
Epoch: 40 Loss: 2.461894989013672
Epoch: 41 Loss: 2.4490602016448975
Epoch: 42 Loss: 2.4348158836364746
Epoch: 43 Loss: 2.4222919940948486
Epoch: 44 Loss: 2.4075124263763428
Epoch: 45 Loss: 2.387392520904541
Epoch: 46 Loss: 2.376638889312744
Epoch: 47 Loss: 2.3616583347320557
Epoch: 48 Loss: 2.349013566970825
Epoch: 49 Loss: 2.339694023132324
Epoch: 50 Loss: 2.3377678394317627
Epoch: 51 Loss: 2.3428919315338135
Epoch: 52 Loss: 2.343137502670288
Epoch: 53 Loss: 2.333061933517456
Epoch: 54 Loss: 2.316023588180542
Epoch: 55 Loss: 2.2908213138580322
Epoch: 56 Loss: 2.277127742767334
Epoch: 57 Loss: 2.2918152809143066
Epoch: 58 Loss: 2.2794125080108643
Epoch: 59 Loss: 2.2864043712615967
Epoch: 60 Loss: 2.235976457595825
Epoch: 61 Loss: 2.2565767765045166
Epoch: 62 Loss: 2.2377259731292725
Epoch: 63 Loss: 2.2317593097686768
Epoch: 64 Loss: 2.219101905822754
Epoch: 65 Loss: 2.178069591522217
Epoch: 66 Loss: 2.2120914459228516
Epoch: 67 Loss: 2.1963396072387695
Epoch: 68 Loss: 2.1773412227630615
Epoch: 69 Loss: 2.2320311069488525
Epoch: 70 Loss: 2.1897146701812744
Epoch: 71 Loss: 2.208383560180664
Epoch: 72 Loss: 2.1805508136749268
Epoch: 73 Loss: 2.1595404148101807
Epoch: 74 Loss: 2.1313321590423584
Epoch: 75 Loss: 2.157655715942383
Epoch: 76 Loss: 2.1123945713043213
Epoch: 77 Loss: 2.1100947856903076
Epoch: 78 Loss: 2.0912978649139404
Epoch: 79 Loss: 2.10208797454834
Epoch: 80 Loss: 2.070941925048828
Epoch: 81 Loss: 2.0449156761169434
Epoch: 82 Loss: 2.036072015762329
Epoch: 83 Loss: 2.035935401916504
Epoch: 84 Loss: 2.018378257751465
Epoch: 85 Loss: 2.0078818798065186
Epoch: 86 Loss: 1.9939370155334473
Epoch: 87 Loss: 1.9931652545928955
Epoch: 88 Loss: 1.9769397974014282
Epoch: 89 Loss: 1.9623976945877075
Epoch: 90 Loss: 1.9500459432601929
Epoch: 91 Loss: 1.9306879043579102
Epoch: 92 Loss: 1.9280986785888672
Epoch: 93 Loss: 1.912978172302246
Epoch: 94 Loss: 1.91163170337677
Epoch: 95 Loss: 1.9094370603561401
Epoch: 96 Loss: 1.9155468940734863
Epoch: 97 Loss: 1.8859769105911255
Epoch: 98 Loss: 1.8756093978881836
```

```
Epoch: 99 Loss: 1.933748483657837
Epoch: 100 Loss: 1.8963221311569214
Epoch: 101 Loss: 1.8538881540298462
Epoch: 102 Loss: 1.8716497421264648
Epoch: 103 Loss: 1.8591663837432861
Epoch: 104 Loss: 1.8466806411743164
Epoch: 105 Loss: 1.8285423517227173
Epoch: 106 Loss: 1.8314367532730103
Epoch: 107 Loss: 1.824350357055664
Epoch: 108 Loss: 1.8195419311523438
Epoch: 109 Loss: 1.8156304359436035
Epoch: 110 Loss: 1.8206208944320679
Epoch: 111 Loss: 1.8188730478286743
Epoch: 112 Loss: 1.7836681604385376
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Epoch: 114 Loss: 1.7880480289459229
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Epoch: 116 Loss: 1.7865631580352783
Epoch: 117 Loss: 1.7687495946884155
Epoch: 118 Loss: 1.7754167318344116
Epoch: 119 Loss: 1.7639377117156982
Epoch: 120 Loss: 1.7484127283096313
Epoch: 121 Loss: 1.7364768981933594
Epoch: 122 Loss: 1.7451560497283936
Epoch: 123 Loss: 1.7264602184295654
Epoch: 124 Loss: 1.7224050760269165
Epoch: 125 Loss: 1.7169432640075684
Epoch: 126 Loss: 1.7193588018417358
Epoch: 127 Loss: 1.702594518661499
Epoch: 128 Loss: 1.7020004987716675
Epoch: 129 Loss: 1.6878840923309326
Epoch: 130 Loss: 1.6794657707214355
Epoch: 131 Loss: 1.6784645318984985
Epoch: 132 Loss: 1.6578580141067505
Epoch: 133 Loss: 1.6573290824890137
Epoch: 134 Loss: 1.6530123949050903
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Epoch: 136 Loss: 1.6553233861923218
Epoch: 137 Loss: 1.6474111080169678
Epoch: 138 Loss: 1.645062804222107
Epoch: 139 Loss: 1.6300501823425293
Epoch: 140 Loss: 1.6362848281860352
Epoch: 141 Loss: 1.655379056930542
Epoch: 142 Loss: 1.6071544885635376
Epoch: 143 Loss: 1.6066522598266602
Epoch: 144 Loss: 1.6111265420913696
Epoch: 145 Loss: 1.5826354026794434
Epoch: 146 Loss: 1.5992677211761475
Epoch: 147 Loss: 1.5954716205596924
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Epoch: 150 Loss: 1.583264708518982
Epoch: 151 Loss: 1.5858384370803833
Epoch: 152 Loss: 1.5906405448913574
Epoch: 153 Loss: 1.5524115562438965
Epoch: 154 Loss: 1.559458613395691
Epoch: 155 Loss: 1.5537687540054321
Epoch: 156 Loss: 1.561966896057129
Epoch: 157 Loss: 1.5453786849975586
Epoch: 158 Loss: 1.5388517379760742
Epoch: 159 Loss: 1.5451080799102783
Epoch: 160 Loss: 1.52116060256958
Epoch: 161 Loss: 1.5245436429977417
Epoch: 162 Loss: 1.5090172290802002
Epoch: 163 Loss: 1.5121647119522095
Epoch: 164 Loss: 1.5065728425979614
```

```
Epoch: 165 Loss: 1.5252405405044556
Epoch: 166 Loss: 1.5153822898864746
Epoch: 167 Loss: 1.4948680400848389
Epoch: 168 Loss: 1.4809225797653198
Epoch: 169 Loss: 1.4876081943511963
Epoch: 170 Loss: 1.4999895095825195
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Epoch: 172 Loss: 1.4767616987228394
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Epoch: 175 Loss: 1.4909617900848389
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Epoch: 177 Loss: 1.4772647619247437
Epoch: 178 Loss: 1.4584388732910156
Epoch: 179 Loss: 1.4575114250183105
Epoch: 180 Loss: 1.4826607704162598
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Epoch: 183 Loss: 1.4690186977386475
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Epoch: 185 Loss: 1.4355392456054688
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Epoch: 187 Loss: 1.4309136867523193
Epoch: 188 Loss: 1.4323457479476929
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Epoch: 194 Loss: 1.4132928848266602
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Epoch: 196 Loss: 1.4282399415969849
Epoch: 197 Loss: 1.4092705249786377
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Epoch: 199 Loss: 1.4217585325241089
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Epoch: 201 Loss: 1.3997554779052734
Epoch: 202 Loss: 1.3949034214019775
Epoch: 203 Loss: 1.3921620845794678
Epoch: 204 Loss: 1.377164363861084
Epoch: 205 Loss: 1.3955243825912476
Epoch: 206 Loss: 1.3882057666778564
Epoch: 207 Loss: 1.3781909942626953
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Epoch: 211 Loss: 1.3836348056793213
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Epoch: 213 Loss: 1.359661340713501
Epoch: 214 Loss: 1.3518846035003662
Epoch: 215 Loss: 1.3377350568771362
Epoch: 216 Loss: 1.3282150030136108
Epoch: 217 Loss: 1.3192921876907349
Epoch: 218 Loss: 1.3248724937438965
Epoch: 219 Loss: 1.3280211687088013
Epoch: 220 Loss: 1.3489458560943604
Epoch: 221 Loss: 1.3439661264419556
Epoch: 222 Loss: 1.334969162940979
Epoch: 223 Loss: 1.3119397163391113
Epoch: 224 Loss: 1.3140571117401123
Epoch: 225 Loss: 1.3070738315582275
Epoch: 226 Loss: 1.311708927154541
Epoch: 227 Loss: 1.3052144050598145
Epoch: 228 Loss: 1.3204797506332397
Epoch: 229 Loss: 1.3070200681686401
Epoch: 230 Loss: 1.2906668186187744
```

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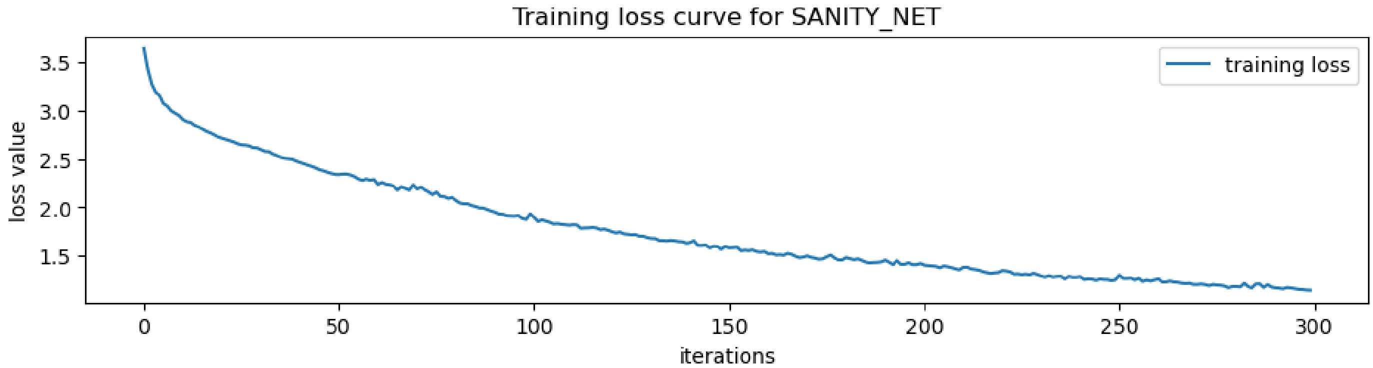
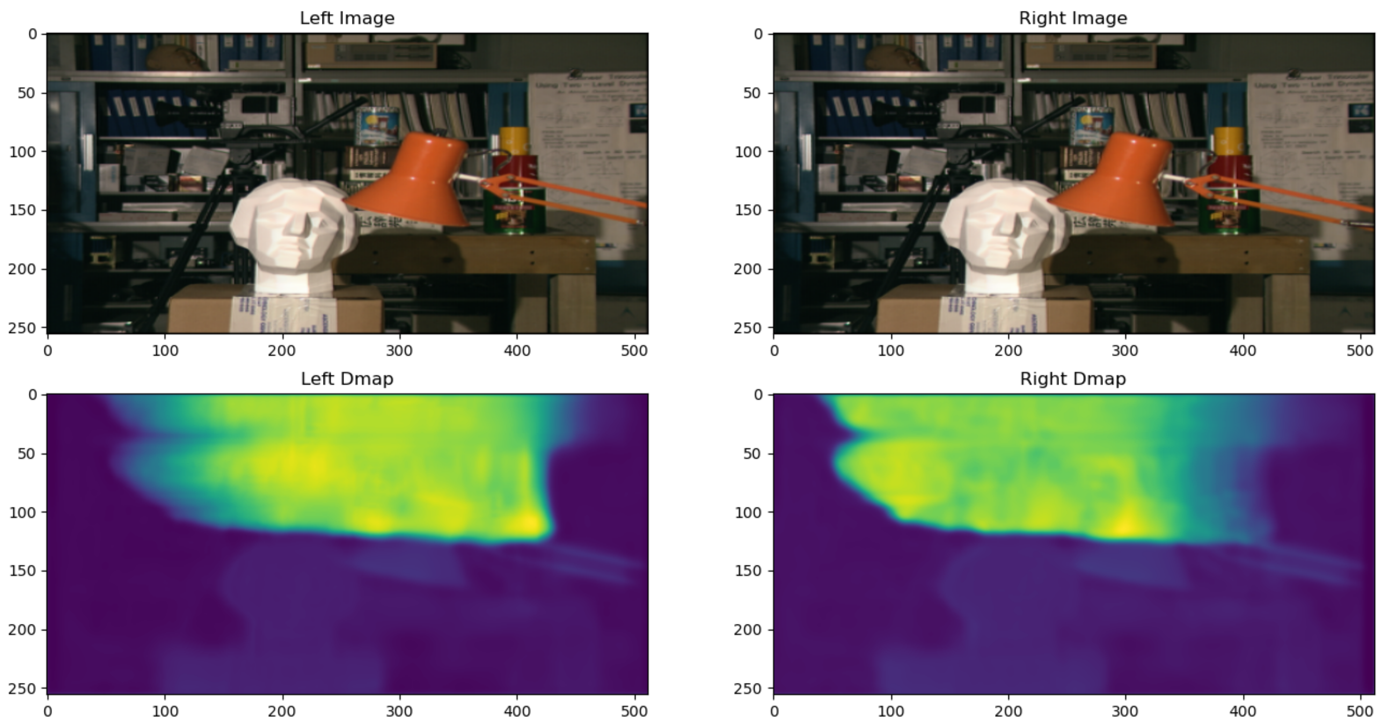
Epoch: 231 Loss: 1.2809864282608032
Epoch: 232 Loss: 1.2953846454620361
Epoch: 233 Loss: 1.2813446521759033
Epoch: 234 Loss: 1.2877036333084106
Epoch: 235 Loss: 1.2901432514190674
Epoch: 236 Loss: 1.2616808414459229
Epoch: 237 Loss: 1.288366436958313
Epoch: 238 Loss: 1.2789949178695679
Epoch: 239 Loss: 1.2786468267440796
Epoch: 240 Loss: 1.2859275341033936
Epoch: 241 Loss: 1.255289912223816
Epoch: 242 Loss: 1.2623928785324097
Epoch: 243 Loss: 1.2593483924865723
Epoch: 244 Loss: 1.2479510307312012
Epoch: 245 Loss: 1.2609840631484985
Epoch: 246 Loss: 1.2560629844665527
Epoch: 247 Loss: 1.2546688318252563
Epoch: 248 Loss: 1.2447043657302856
Epoch: 249 Loss: 1.2526838779449463
Epoch: 250 Loss: 1.3015516996383667
Epoch: 251 Loss: 1.2671116590499878
Epoch: 252 Loss: 1.267642855644226
Epoch: 253 Loss: 1.2710000276565552
Epoch: 254 Loss: 1.2516310214996338
Epoch: 255 Loss: 1.2689288854599
Epoch: 256 Loss: 1.2361496686935425
Epoch: 257 Loss: 1.2507116794586182
Epoch: 258 Loss: 1.24008309841156
Epoch: 259 Loss: 1.2520041465759277
Epoch: 260 Loss: 1.2619812488555908
Epoch: 261 Loss: 1.2308140993118286
Epoch: 262 Loss: 1.230446696281433
Epoch: 263 Loss: 1.2401058673858643
Epoch: 264 Loss: 1.2303446531295776
Epoch: 265 Loss: 1.2274514436721802
Epoch: 266 Loss: 1.2180416584014893
Epoch: 267 Loss: 1.2154881954193115
Epoch: 268 Loss: 1.2181802988052368
Epoch: 269 Loss: 1.2054592370986938
Epoch: 270 Loss: 1.2048587799072266
Epoch: 271 Loss: 1.2096879482269287
Epoch: 272 Loss: 1.203872561454773
Epoch: 273 Loss: 1.1925560235977173
Epoch: 274 Loss: 1.2048609256744385
Epoch: 275 Loss: 1.1983803510665894
Epoch: 276 Loss: 1.1969114542007446
Epoch: 277 Loss: 1.1893131732940674
Epoch: 278 Loss: 1.1717450618743896
Epoch: 279 Loss: 1.184215784072876
Epoch: 280 Loss: 1.183860182762146
Epoch: 281 Loss: 1.1803715229034424
Epoch: 282 Loss: 1.2176382541656494
Epoch: 283 Loss: 1.1824841499328613
Epoch: 284 Loss: 1.1695640087127686
Epoch: 285 Loss: 1.2099241018295288
Epoch: 286 Loss: 1.2118604183197021
Epoch: 287 Loss: 1.1739060878753662
Epoch: 288 Loss: 1.203137755393982
Epoch: 289 Loss: 1.177927851676941
Epoch: 290 Loss: 1.1698569059371948
Epoch: 291 Loss: 1.1669492721557617
Epoch: 292 Loss: 1.1605147123336792
Epoch: 293 Loss: 1.1733492612838745
Epoch: 294 Loss: 1.1692477464675903
Epoch: 295 Loss: 1.1621052026748657
Epoch: 296 Loss: 1.1549689769744873
```

```
Epoch: 297 Loss: 1.1520713567733765
Epoch: 298 Loss: 1.1473761796951294
Epoch: 299 Loss: 1.145646095275879
CPU times: user 11min 52s, sys: 1min 47s, total: 13min 40s
Wall time: 12min 56s
```



In [44]:

```python
# Test the untrained network on some sample images
dmap = display_disparity(sanity_net, sanity_dataset, 0)
```



We can see that apart from the big green blob, the rest of the disparity map is looking as expected. To be specific, we can make out the shape of the lamp and the figure head, which is really great! If you look closer, we can see outlines of the table as well.

So overall, we can see four different disparity levels (in order of depth): lamp, figure head, table, background, which I am happy about.

Now, let's discuss the big green blob. I'm not entirely sure why it's there. I would re-run if I had more time, but unfortunately I don't. If I had to speculate about why it's there, it might have something to do with our learning model getting stuck in an unseen minima, which it can't get out of.

I also would like to comment on the training loss curve, which is decreasing with more epochs, as expected.

If I had more time, I would definitely use the multi-threading capabilities of the NVIDIA GPU. I unfortunately have an older machine, and Google Colab was taking a very long time to upload all my data onto.

Training on the entire training dataset (1059 images)

In [ ]:

```
%%time
%matplotlib notebook
%matplotlib inline

train_net = MyNet().to(device)

# set loss function for the net
train_net.criterion = monocularDepthLoss(device).to(device)

loader = train_loader
optimizer = torch.optim.Adam(train_net.parameters(), lr=0.01)

EPOCH = 3

# switch to train mode
train_net.train()

print("Starting Training...")

loss_graph = []

fig = plt.figure(figsize=(12,6))
plt.subplots_adjust(bottom=0.2,right=0.85,top=0.5)
ax = fig.add_subplot(1,1,1)

for e in range(EPOCH):
    loss = train(loader, train_net, optimizer, loss_graph)
    ax.clear()
    ax.set_xlabel('iterations')
    ax.set_ylabel('loss value')
    ax.set_title('Training loss curve for TRAIN_NET')
    ax.plot(loss_graph, label='training loss')
    ax.legend(loc='upper right')
    fig.canvas.draw()
    print("Epoch: {} Loss: {}".format(e, loss))
```