ECE471, Selected Topics in Machine Learning – Midterm Learning to See in the Dark Nikola Janjušević October 25, 2018

Goal

This assignment was an attempt to replicate the results of the paper: Learning to See in the Dark [1], in which the group trains a fully convolutional neural network to infer a properly exposed RGB image from an input, severely underexposed, RAW image. The Seeing in the Dark (SID) group's code can be seen at https://github.com/cchen156/Learning-to-See-in-the-Dark

Remarks

RAW files are large. I decided to decimate my input RAW files and ground truth PNGs by a factor of 16 so that all the training images could be easily loaded into memory. It is possible that this decimation ruins the set up that makes the SID group's results possible, namely, the spatial context from the original RAW file may be lost.

Sad (approaching not sad) Results

After 100+ epochs, my network stagnated, producing only brown squares. I then changed some hyper parameters around, including input patch-size, activation function, kernel initialization, and annealed learning rates. I was then able to train to a much lower average cost, but the model still stagnates at a relatively high value. Further investigation is needed to train further. My next step, if time was permitting, would be to apply further data-augmentation (as performed in the paper). **Note**: input images are not shown as they are essentially black to the human eye.



Figure 1: 20 epochs, activation fcn: relu6, patch-size: 32



Figure 2: 40 epochs, activation fcn: relu, xavier init, patch-size: 64



Figure 3: 100 epochs, activation fcn: relu, xavier init, patch-size: 64

References

Program: sid2.py

```
1 #!/usr/bin/python3
   import time
   import scipy as sp
4 import scipy.misc
   import matplotlib.pyplot as plt
6 import pandas
7
   import imageio
8 \quad \mathtt{import} \quad \mathtt{numpy} \quad \mathtt{as} \quad \mathtt{np}
9 \quad \mathtt{import \ tensorflow \ as \ tf}
10 \quad {\tt from \ tqdm \ import \ tqdm}
11 import rawpy
12 import os, glob
13 os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
14
15 SIZE_REDUCTION = 16
16 logs_dir = './logs/'
17 tflog = logs_dir + 'tflog'
18 logfile = logs_dir + 'log.txt'
19 check_point_dir = './ckpnt/'
20 in_dir = 'DWN%d/short/'%SIZE_REDUCTION
21 \text{ gt\_dir}
           = 'DWN%d/long/'%SIZE_REDUCTION
22
23 # hyper-parameters
24 BATCH_SIZE = 1
25 NUM_EPOCHS = 4000
26 \text{ SAVE\_RATE} = 20
27 DISP_RATE = 1
28 \text{ LR\_DECAY\_RATE} = 40
29 LEARNING_RATE = 1e-3
30 \text{ PATCH\_SIZE} = 64
31
33 # ----- NETWORK -----
34 # ------
35
36 # activation fcn used in architecture
37 def act(x):
38
       return tf.nn.relu(x)
39
40 def conv(x,chan,ksz):
41
       return tf.layers.conv2d(x,chan,ksz,padding='SAME',activation=act,
42
            kernel_initializer=tf.contrib.layers.xavier_initializer())
43
44 # contraction module of UNET
45 def contract_mod(x,chans=None):
46
       num_fchans = 2*int(x.shape[-1]) if chans==None else chans
47
       c = conv(x,num_fchans,3)
48
       c = conv(c,num_fchans,3)
49
       p = tf.layers.max_pooling2d(c,2,2,padding='SAME')
50
       return c,p
51
52 # upsample in1, concatenate both inputs
53 # output 2*c feature channels
54 def upsample_cat(in1,in2,c):
55
       ups = tf.layers.conv2d_transpose(in1,c,2,2,padding='SAME')
56
        x = tf.concat([ups,in2],3)
57
       return x
58
59 # expansion module of UNET
60 \quad \textit{\# input1 upsample connection, input2 concat connection}
61 \ \text{def expand\_mod(input1,input2):}
62
       out_chans= input2.get_shape()[-1]
63
       x = upsample_cat(input1,input2,out_chans)
       x = conv(x,out_chans,3)
```

```
65
       x = conv(x,out_chans,3)
66
       return x
67
68
   # UNET ARCHITECTURE
   def f(x):
69
70
       # contract
71
       c1,p1 = contract_mod(x,chans=32)
72
       c2,p2 = contract_mod(p1)
       c3,p3 = contract_mod(p2)
73
74
       c4,p4 = contract_mod(p3)
75
       c5, _ = contract_mod(p4)
76
       # expand
77
       e1 = expand_mod(c5, c4)
78
       e2 = expand_mod(e1,c3)
79
       e3 = expand_mod(e2,c2)
80
       e4 = expand_mod(e3,c1)
       # out of UNET
81
82
       sub = tf.layers.conv2d(e4,12,1,padding='SAME')
83
       # depth2space == subpixel reconstruction
       # out chans = 12/(2*2) = 3 <-- perfect!
84
85
       out = tf.depth_to_space(sub,2)
86
       return out
87
88 # learning rate
89 lr = tf.placeholder(tf.float32)
90 # input, truth, est.
91 x = tf.placeholder(tf.float32, shape=[None,None,Mone,4])
92 y = tf.placeholder(tf.float32, shape=[None,None,None,3])
93 \text{ y_hat = } f(x)
94
95 # -----
96 # ----- FILES -----
97 # -----
98
99 gt_fns = glob.glob(gt_dir+'*')
100 in_fns = glob.glob(in_dir+'*')
101 train_ids = [int(os.path.basename(fn)[0:5]) for fn in gt_fns]
102 [ x.sort() for x in [gt_fns, in_fns, train_ids] ]
103 # exposure ratios
104 ratios = np.empty((len(train_ids)))
105 for i in range(len(train_ids)):
106
       ratios[i] = float(os.path.basename(gt_fns[i])[9:-5]) / \
107
           float(os.path.basename(in_fns[i])[9:-5])
108 print(ratios[0])
109 print('Loading data...')
110
   start_time = time.time()
111
112 gt_imgs = np.stack( [scipy.misc.imread(x) for x in gt_fns] )
113 in_imgs = np.stack( [np.load(x) for x in in_fns] )
114 # subtracting black level and normalizing to [0,1] scale
115 in_imgs = np.maximum(in_imgs-512,0) / (16383-512)
116
117 time_elapsed = time.time() - start_time
118 print('%3fs to load data'%time_elapsed)
119
120 # demo of batches
121 \# yb = qt_imqs[0,:,:,:]
122 \text{ # } xb = in\_imgs[0,:,:,0]
123 # print(xb.shape, yb.shape)
124 # figure, (ax1, ax2) = plt.subplots(1,2)
125 # ax1.imshow(np.squeeze(xb))
126 # ax2.imshow(np.squeeze(yb))
127 # plt.show()
128
   # -----
129
130 # ----- DATA -----
```

```
131 # ------
132
   # pk: input image in pack form
133
134
   # gt: ground truth image (in sRGB)
135
   # ps: patch size (square)
   # a patch of the packed bayers corresponds to a patch
136
   # of the full size image (gt) that is twice as large
137
    def to_patch(pk,gt,ps=PATCH_SIZE):
138
139
       H = pk.shape[0]
140
       W = pk.shape[1]
141
       h = np.random.randint(H-ps)
142
       w = np.random.randint(W-ps)
143
       pk_patch = pk[h:(h+ps),
                                 w:(w+ps),
144
       gt_patch = gt[2*h:2*(h+ps), 2*w:2*(w+ps),:]
145
       return pk_patch, gt_patch
146
147 def batch_to_patch(xb,yb,ps=PATCH_SIZE):
148
       xp = []
149
       yp = []
150
       H = xb.shape[1]
151
       W = xb.shape[2]
152
       for i in range(xb.shape[0]):
153
           h = np.random.randint(H-ps)
154
            w = np.random.randint(W-ps)
155
           xp.append(xb[i, h:(h+ps),
                                         w:(w+ps),
           yp.append(yb[i, 2*h:2*(h+ps), 2*w:2*(w+ps),:])
156
        return np.stack(xp), np.stack(yp)
157
158
159
    def get_batch():
160
        choices = np.random.choice(len(train_ids),size=BATCH_SIZE)
161
        rb = ratios[choices] # batch of ratios
162
        xb, yb = batch_to_patch(in_imgs[choices,:,:,:], gt_imgs[choices,:,:,:])
163
        for i in range(BATCH_SIZE):
164
           xb[i,:,:,:] = xb[i,:,:,:]*rb[i]
165
        return xb, yb
166
167 # demo of batches
168 \# xb, yb = get\_batch()
169 # print(xb.shape, yb.shape)
170 # figure, (ax1, ax2) = plt.subplots(1,2)
   # ax1.imshow(np.squeeze(xb[0,:,:,0]))
171
172 # ax2.imshow(np.squeeze(yb[0,:,:,:]))
173 # plt.show()
174
175
176
   # ----- TRAINING -----
    # -----
177
178
179
180 # L1 LOSS ONLY
181 loss = tf.reduce_mean( tf.abs(y_hat - y) )
182 optim = tf.train.AdamOptimizer(learning_rate=lr).minimize(loss)
183 init = tf.global_variables_initializer()
184
185 # Create a summary to monitor cost tensor
186 tf.summary.scalar("loss", loss)
187 # Create a summary to monitor accuracy tensor
188 # tf.summary.scalar("accuracy", accuracy)
189 # Merge all summaries into a single op
190 merged_summary_op = tf.summary.merge_all()
191
192 with tf.Session() as sess:
193
       sess.run(init)
194
195
        # op to write logs to Tensorboard
196
        summary_writer = tf.summary.FileWriter(tflog,
```

```
197
            graph=tf.get_default_graph())
198
        learning_rate = LEARNING_RATE
199
        # training
200
        st = time.time()
201
        for epoch in range(NUM_EPOCHS):
202
            avg_cost = 0.
203
            num_batches = int( np.ceil( len(train_ids) / BATCH_SIZE ) )
204
            if (epoch+1)%LR_DECAY_RATE == 0:
205
206
                learning_rate = learning_rate*.1
207
208
            for i in tqdm(range(num_batches)):
209
                xb, yb = get_batch()
210
                fd = {x: xb, y: yb, lr: learning_rate}
211
                output, loss_np, _, summary \
212
                     = sess.run([y_hat, loss, optim, merged_summary_op], feed_dict=fd)
213
                 # logs every batch
214
                summary_writer.add_summary(summary, epoch * num_batches + i)
215
                avg_cost += loss_np/num_batches
216
217
            # save output of part of batch
218
            if (epoch+1) % SAVE_RATE == 0:
219
                cat = np.concatenate((output[0,:,:,:],yb[0,:,:,:]),axis=1)
220
                scipy.misc.imsave(logs_dir + '%04d.jpg'%(epoch+1), cat)
221
222
            # log to stdout at each epoch
            if (epoch+1) % DISP_RATE == 0:
223
224
                print('Time: %06f, Epoch: %03d, Cost: %5ld'%(time.time()-st,epoch+1,
                    avg_cost))
225
226
            # print('Validation Set Accuracy:',
227
                 \# accuracy.eval(\{x: data.x\_val, y: data.y\_val, phase: False\}))
228
229
        print("Run the command line:\n--> tensorboard --logdir=./tf_logs ")
```