計算機視覺作業

干皓丞，2101212850, 信息工程學院

2021 年 11 月 9 日

1　作業目標與章節摘要

在 GitHub 或者任意頁面下載超分算法，獲得結果試著訓練 1　2 個 Epoch，並給出分析結果，原始程式碼在名為 kancheng/kan-cs-report-in-2021 的 Github 專案下，可以在 CV/super-resolution/code 下找到。

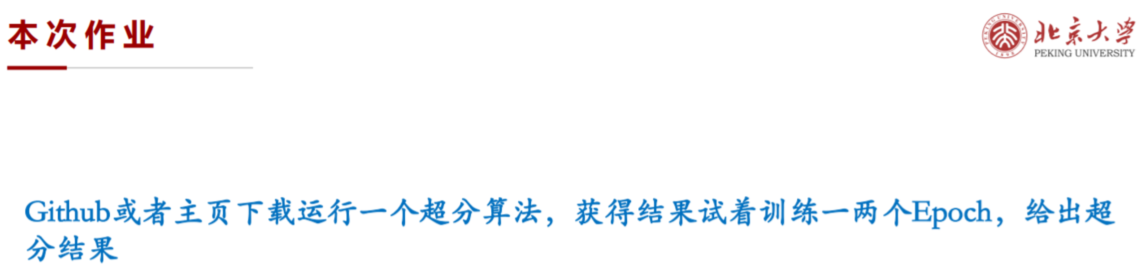


Fig. 1. 作業目標

2　Practice CNN

在此將上次課程的範例與 MNIST 做一個練習，可以在專案目錄 CV/super-resolution/code 下找到名為 cnn-each-init-method.ipynb 的檔案，該剛檔案對範例的 LeNet、AlexNet、VGG、GoogLeNet、ResNet、ShuffleNet、Res2Net、DenseNet 等，CNN 程式碼進行複習，對應後面的超分算法 SRCNN 會比較有感覺。

3　Pytorch SRCNN

Pytorch SRCNN 分為兩類，一個為 Pytorch 撰寫的 *.py 檔案，在 CV/super-resolution/code 下的 pytorch-srcnn，可以直接用指令執行，同時額外寫一個版本為 *.ipynb，方便進行呈現，檔名為 pytorch-srcnn-demo.ipynb。該專案測試訓練資料的放置於 kancheng/training-data 下的相同名稱的目錄。兩個版本的差異在於目錄配置不同。其兩者的目錄檔案目錄配置如下。input 目錄為放置訓練測試資料，outputs 為放置輸出結果，而 *.py 版本則是有一個名為 src 的目錄，當中分別為代表 SRCNN 的 srcnn.py、訓練的 train.py 與測試的 test.py，而 *.ipynb 版本則為單純的呈現，為了證明可執行 Epoch 值在 pytorch-srcnn-demo.ipynb 中設定為，而 *.py 則是有 Epoch 值設定為 100，後續呈現程式碼的部分為 *.ipynb 的版本，而測試結果為 *.py 的版本。

下為 Pytorch SRCNN 的 *.py 與 *.ipynb 版本目錄配置。

```
# *.py 版本

├── input
│   ├── Set5
│   ├── T91
│   ├── bicubic_2x
│   └── train_mscale.h5
├── outputs
└── src
    ├── __pycache__
    ├── srcnn.py
    ├── test.py
    └── train.py

# *.ipynb 版本

├── input
│   ├── Set5
│   ├── T91
│   ├── bicubic_2x
│   └── train_mscale.h5
├── outputs
└── pytorch-srcnn-demo.ipynb
```

Fig. 2. Pytorch SRCNN 目錄配置

Pytorch SRCNN 的程式碼如下所示。

```python
import torch.nn as nn
import torch.nn.functional as F
class SRCNN(nn.Module):
    def __init__(self):
        super(SRCNN, self).__init__()
        self.conv1 = nn.Conv2d(1, 64, kernel_size=9, padding=2,
            padding_mode='replicate')
        # padding mode same as original Caffe code
        self.conv2 = nn.Conv2d(64, 32, kernel_size=1, padding=2,
            padding_mode='replicate')
        self.conv3 = nn.Conv2d(32, 1, kernel_size=5, padding=2,
            padding_mode='replicate')
    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = self.conv3(x)
        return x
import torch
import matplotlib
import matplotlib.pyplot as plt
import time
import h5py
# import srcnn
```

```
import torch.optim as optim
import torch.nn as nn
import numpy as np
import math
from torch.utils.data import DataLoader, Dataset
from tqdm import tqdm
from sklearn.model_selection import train_test_split
from torchvision.utils import save_image
matplotlib.style.use('ggplot')

# learning parameters
batch_size = 64 # batch size, reduce if facing OOM error
epochs = 2
# epochs = 100
# number of epochs to train the SRCNN model for
lr = 0.001 # the learning rate
device = 'cuda' if torch.cuda.is_available() else 'cpu'

# input image dimensions
img_rows, img_cols = 33, 33
out_rows, out_cols = 33, 33

# file = h5py.File('../input/train_mscale.h5')
file = h5py.File('./input/train_mscale.h5')
# `in_train` has shape (21884, 33, 33, 1) which corresponds to
# 21884 image patches of 33 pixels height & width and 1 color channel
in_train = file['data'][:] # the training data
out_train = file['label'][:] # the training labels
file.close()
# change the values to float32
in_train = in_train.astype('float32')
out_train = out_train.astype('float32')

(x_train, x_val, y_train, y_val) = train_test_split(in_train, out_train,
    test_size=0.25)
print('Training samples: ', x_train.shape[0])
print('Validation samples: ', x_val.shape[0])

# the dataset module
class SRCNNDataset(Dataset):
    def __init__(self, image_data, labels):
```

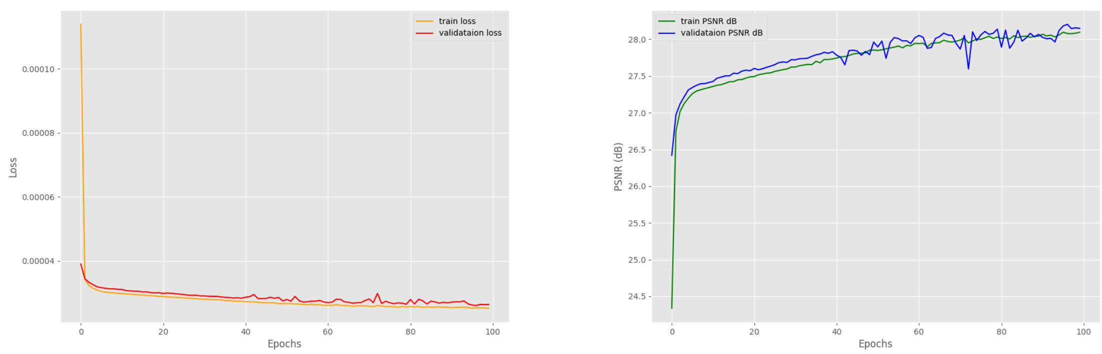
```
        self.image_data = image_data
        self.labels = labels
    def __len__(self):
        return (len(self.image_data))
    def __getitem__(self, index):
        image = self.image_data[index]
        label = self.labels[index]
        return (
            torch.tensor(image, dtype=torch.float),
            torch.tensor(label, dtype=torch.float)
        )


# train and validation data
train_data = SRCNNDataset(x_train, y_train)
val_data = SRCNNDataset(x_val, y_val)
# train and validation loaders
train_loader = DataLoader(train_data, batch_size=batch_size)
val_loader = DataLoader(val_data, batch_size=batch_size)

# initialize the model
print('Computation device: ', device)
model = SRCNN().to(device)
print(model)

# optimizer
optimizer = optim.Adam(model.parameters(), lr=lr)
# loss function
criterion = nn.MSELoss()

def psnr(label, outputs, max_val=1.):
    """
    Compute Peak Signal to Noise Ratio (the higher the better).
    PSNR = 20 * log10(MAXp) - 10 * log10(MSE).
    https://en.wikipedia.org/wiki/Peak_signal-to-noise_ratio#Definition
    First we need to convert torch tensors to NumPy operable.
    """
    label = label.cpu().detach().numpy()
    outputs = outputs.cpu().detach().numpy()
    img_diff = outputs - label
    rmse = math.sqrt(np.mean((img_diff) ** 2))
```

```
    if rmse == 0:
        return 100
    else:
        PSNR = 20 * math.log10(max_val / rmse)
        return PSNR



def train(model, dataloader):
    model.train()
    running_loss = 0.0
    running_psnr = 0.0
    for bi, data in tqdm(enumerate(dataloader), total=int(len(train_data)
       /dataloader.batch_size)):
        image_data = data[0].to(device)
        label = data[1].to(device)

        # zero grad the optimizer
        optimizer.zero_grad()
        outputs = model(image_data)
        loss = criterion(outputs, label)
        # backpropagation
        loss.backward()
        # update the parameters
        optimizer.step()
        # add loss of each item (total items in a batch = batch size)
        running_loss += loss.item()
        # calculate batch psnr (once every `batch_size` iterations)
        batch_psnr =  psnr(label, outputs)
        running_psnr += batch_psnr
    final_loss = running_loss/len(dataloader.dataset)
    final_psnr = running_psnr/int(len(train_data)/dataloader.batch_size)
    return final_loss, final_psnr


def validate(model, dataloader, epoch):
    model.eval()
    running_loss = 0.0
    running_psnr = 0.0
    with torch.no_grad():
        for bi, data in tqdm(enumerate(dataloader), total=int(len(
```

```
                val_data)/dataloader.batch_size)):
            image_data = data[0].to(device)
            label = data[1].to(device)

            outputs = model(image_data)
            loss = criterion(outputs, label)
            # add loss of each item (total items in a batch = batch size)
            running_loss += loss.item()
            # calculate batch psnr (once every `batch_size` iterations)
            batch_psnr = psnr(label, outputs)
            running_psnr += batch_psnr
        outputs = outputs.cpu()
        save_image(outputs, f"./outputs/val_sr{epoch}.png")
    final_loss = running_loss/len(dataloader.dataset)
    final_psnr = running_psnr/int(len(val_data)/dataloader.batch_size)
    return final_loss, final_psnr


train_loss, val_loss = [], []
train_psnr, val_psnr = [], []
start = time.time()
for epoch in range(epochs):
    print(f"Epoch {epoch + 1} of {epochs}")
    train_epoch_loss, train_epoch_psnr = train(model, train_loader)
    val_epoch_loss, val_epoch_psnr = validate(model, val_loader, epoch)
    print(f"Train PSNR: {train_epoch_psnr:.3f}")
    print(f"Val PSNR: {val_epoch_psnr:.3f}")
    train_loss.append(train_epoch_loss)
    train_psnr.append(train_epoch_psnr)
    val_loss.append(val_epoch_loss)
    val_psnr.append(val_epoch_psnr)
end = time.time()
print(f"Finished training in: {((end-start)/60):.3f} minutes")


# loss plots
plt.figure(figsize=(10, 7))
plt.plot(train_loss, color='orange', label='train loss')
plt.plot(val_loss, color='red', label='validataion loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```python
plt.legend()
plt.savefig('./outputs/loss.png')
plt.show()
# psnr plots
plt.figure(figsize=(10, 7))
plt.plot(train_psnr, color='green', label='train PSNR dB')
plt.plot(val_psnr, color='blue', label='validataion PSNR dB')
plt.xlabel('Epochs')
plt.ylabel('PSNR (dB)')
plt.legend()
plt.savefig('./outputs/psnr.png')
plt.show()
# save the model to disk
print('Saving model...')
torch.save(model.state_dict(), './outputs/model.pth')
```

從測試結果中可以看到 Epochs 設定為 100 時，Train Loss 很快的下降，同時 PSNR 也平穩，同時也可以從訓練後的結果中可看到相對原本清晰的結果。若 Epochs 設定更高時，或許可以有更好的結果。而訓練與測試過程中的指令輸出結果則被記錄在專案目錄下的 command-line-record.md 檔案。



(i) Train Loss (ii) PSNR

Fig. 3. 訓練

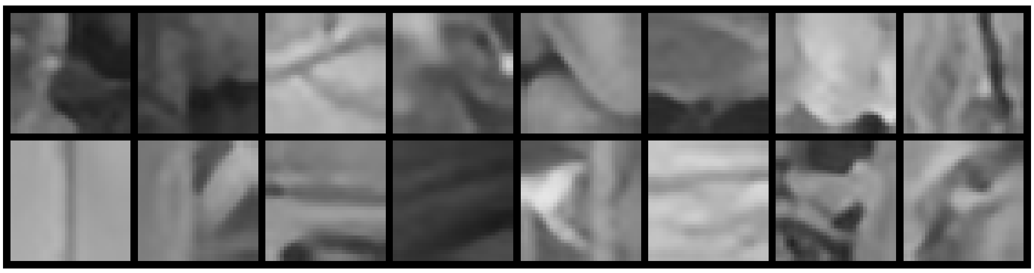
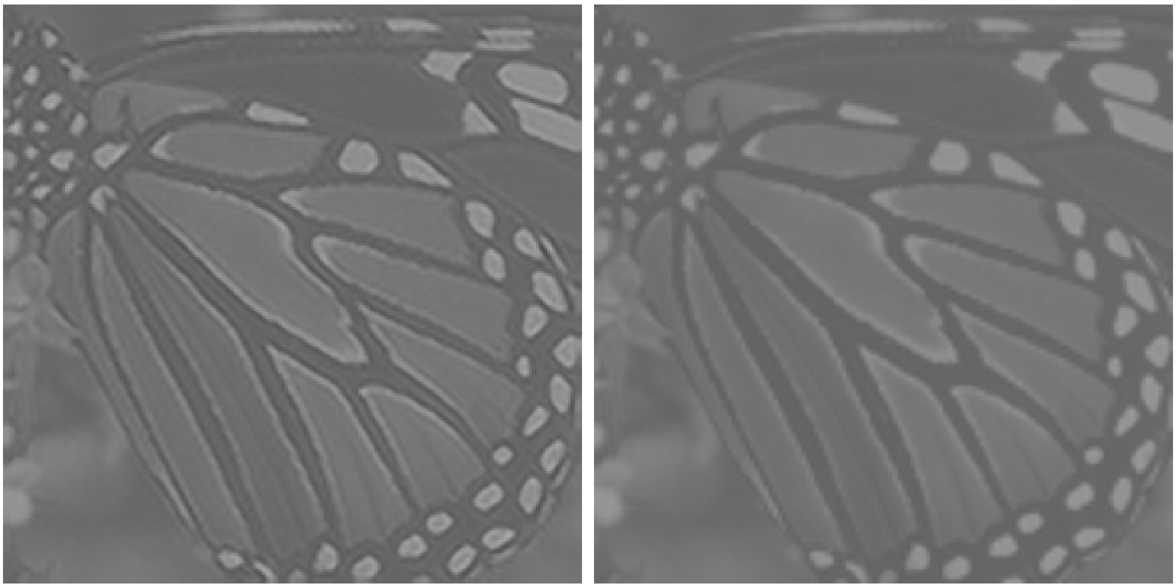


Fig. 4. Pytorch SRCNN 訓練過程



(i) Output (ii) Test

Fig. 5. 輸出測試結果

Epoch	Train PSNR	Val PSNR
10	27.343	27.413
20	27.489	27.572
30	27.622	27.723
40	27.734	27.832
50	27.854	27.963
60	27.945	28.022
70	27.974	27.945
80	28.032	28.139
90	28.043	28.068
100	28.097	28.149

4 Tensorflow SRCNN

Tensorflow SRCNN 在此為單純的 *.py 檔案，在 CV/super-resolution/code 下的 tensorflow-srcnn，可以直接用指令執行。該專案測試訓練資料的放置於 kancheng/training-data 下的相同名稱的目錄，而訓練與測試過程中的指令輸出結果則被記錄在專案目錄下的 command-line-record.md 檔案。當中需要注意的是 Mac 使用者很有可能會在測試時遇到.DS_store 的問題，建議可以使用指令進行暫時性處理。另外若想要放置自己測試的資料必須放在該專案目錄下的 Test 目錄，同時要符合該專案的結構。

```
$ sudo find /Users/[ Path ]/ -name ".DS_Store" -depth -exec rm {} \;
```

同時在測試與訓練過程需要注意的地方在於，參與預設的細節另外，其參數範例如下所示。

```
# Training SRCNN
# Quick training
$ python main.py

# Example usage
$ python main.py --use_pretrained=False \
    --epoch=1000 \
    --scale=4 \

# Testing SRCNN
# Quick testing
$ python main.py --is_training=False \
    --use_pretrained=True

# Example usage
$ python main.py --is_training=False \
    --use_pretrained=True \
    --test_dataset=YOUR_DATASET \
    --scale=4

# 若想自行加入資料
#  Test 为測試資料目录名稱
$ python main.py --is_training=False \
    --use_pretrained=True \
    --test_dataset=Test \
    --scale=4
```

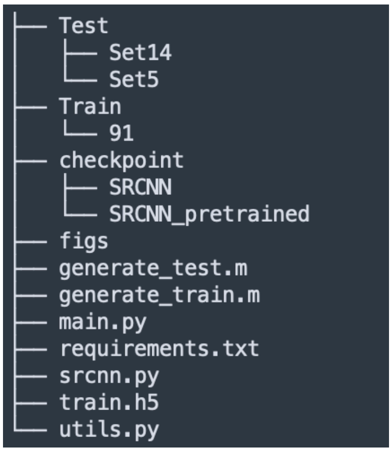


Fig. 6. Tensorflow SRCNN 目錄配置

main.py 程式碼如下所示。

```
# import tensorflow as tf
import tensorflow
import tensorflow.compat.v1 as tf
from srcnn import SRCNN


# flags = tf.app.flags
flags = tf.compat.v1.app.flags
flags.DEFINE_integer('epoch', 10000, 'Number of epoch')
flags.DEFINE_integer('batch_size', 128, 'The size of batch images')
flags.DEFINE_integer('image_size', 33, 'The size of sub-image')
flags.DEFINE_integer('label_size', 21, 'The size of label')

flags.DEFINE_integer('scale', 3, 'The up-scale value for training and testing')

flags.DEFINE_float('learning_rate', 1e-4, 'The learning rate of gradient descent algorithm')
flags.DEFINE_float('beta1', 0.9, 'The momentum value of gradient descent algorithm')

flags.DEFINE_string('valid_dataset', 'Set5', 'The name of training dataset')
flags.DEFINE_string('test_dataset_path', 'Test', 'The path of test dataset')
flags.DEFINE_string('test_dataset', 'Set5', 'The name of testing dataset')

```

```
flags.DEFINE_string('checkpoint_path', 'checkpoint', 'The path of
    checkpoint directory')
flags.DEFINE_boolean('use_pretrained', False, 'True for use pre-trained
    model, False for train on your own')
flags.DEFINE_string('result_dir', 'result', 'The path to save result
    images')
flags.DEFINE_boolean('is_training', True, 'True for training, False for
    testing')

FLAGS = flags.FLAGS


def main(_):
    with tf.Session() as sess:
        srcnn = SRCNN(sess, FLAGS)

        if FLAGS.is_training == True:
            srcnn.train(FLAGS)

        elif FLAGS.is_training == False:
            srcnn.test(FLAGS)

        else:
            print('[*] Please give correct [is_training] value ')

if __name__ == '__main__':
    tf.app.run()
```

srcnn.py 程式碼如下所示。

```
import tensorflow as tf
import numpy as np

import os
import time
from tqdm import tqdm

from utils import *


class SRCNN(object):
    def __init__(self, sess, config):
```

```python
        self.sess = sess

        # The size of training sub-images is 33
        # All the convolutional layers have no padding (fsub-f1-f2-f3+3) = (33-5-9-1+3) = 21
        self.image_size = [None, None, None, 1]
        self.label_size = [None, None, None, 1]

        self.build_model()


    def build_model(self):
        self.images = tf.placeholder(tf.float32, self.image_size, name='images')
        self.labels = tf.placeholder(tf.float32, self.label_size, name='labels')

        self.weights = {
            'w1': tf.Variable(tf.random_normal([9, 9, 1, 64], stddev=0.001), name='w1'),
            'w2': tf.Variable(tf.random_normal([1, 1, 64, 32], stddev=0.001), name='w2'),
            'w3': tf.Variable(tf.random_normal([5, 5, 32, 1], stddev=0.001), name='w3')
        }
        self.biases = {
            'b1': tf.Variable(tf.zeros([64]), name='b1'),
            'b2': tf.Variable(tf.zeros([32]), name='b2'),
            'b3': tf.Variable(tf.zeros([1]), name='b3')
        }

        self.forward = self.model()

        # Loss Function : Mean Square Error
        self.loss = tf.reduce_mean(tf.square(tf.subtract(self.labels, self.forward)))

        # Clip output
        self.result = tf.clip_by_value(self.forward, clip_value_min=0., clip_value_max=1.)

```

```
        self.saver = tf.train.Saver()


    # Input  : (33 x 33 x 1)
    # Layer1 : (9 x 9 x 1 x 64)
    # Layer2 : (1 x 1 x 64 x 32)
    # Layer3 : (5 x 5 x 32 x 1)
    # Output : (21 x 21 x 1)
    def model(self):
        conv1 = tf.nn.relu(tf.nn.bias_add(tf.nn.conv2d(self.images, self.weights['w1'], strides=[1,1,1,1], padding='VALID'), self.biases['b1']))

        conv2 = tf.nn.relu(tf.nn.bias_add(tf.nn.conv2d(conv1, self.weights['w2'], strides=[1,1,1,1], padding='VALID'), self.biases['b2']))

        output = tf.nn.bias_add(tf.nn.conv2d(conv2, self.weights['w3'], strides=[1,1,1,1], padding='VALID'), self.biases['b3'])

        return output


    def train(self, config):
        print('[*] SRCNN training will be started ! ')

        if not exist_train_data():
            print('[!] No train data ready .. Please generate train data first with Matlab')
            return
        else:
            train_images, train_labels = load_train_data()
            print('[*] Successfully load train data ! ')

        valid_images, valid_labels = prepare_data(config, is_valid=True)

        # Adam optimizer with the standard backpropagation
        # The learning rate is 1e-4 for the first two layers, and 1e-5 for the last layer
        # beta1 is 0.9 in paper
        var_list1 = [self.weights['w1'], self.weights['w2'], self.biases[
```

```
'b1'], self.biases['b2']]
        var_list2 = [self.weights['w3'], self.biases['b3']]
        opt1 = tf.train.AdamOptimizer(config.learning_rate, beta1=config.
            beta1)
        opt2 = tf.train.AdamOptimizer(config.learning_rate * 0.1, beta1=
            config.beta1)
        grads = tf.gradients(self.loss, var_list1 + var_list2)
        grads1 = grads[:len(var_list1)]
        grads2 = grads[len(var_list1):]
        train_op1 = opt1.apply_gradients(zip(grads1, var_list1))
        train_op2 = opt2.apply_gradients(zip(grads2, var_list2))
        self.train_op = tf.group(train_op1, train_op2)

        #self.train_op = tf.train.AdamOptimizer(self.learning_rate).
            minimize(self.loss)

        # Initialize TensorFlow variables
        init = tf.global_variables_initializer()
        self.sess.run(init)

        # Load checkpoint
        self.load(config)

        start_time = time.time()
        bicubic_psnr = []
        print('[*] Start training ... Please be patient !')
        for i in tqdm(range(config.epoch), desc='[*] Keep going ! ',
            leave=True):
            loss = 0
            batch_idxs = len(train_images) // config.batch_size

            for idx in range(batch_idxs):
                batch_images = train_images[idx*config.batch_size : (idx
                    +1)*config.batch_size]
                batch_labels = train_labels[idx*config.batch_size : (idx
                    +1)*config.batch_size]

                _, err = self.sess.run([self.train_op, self.loss],
                    feed_dict={self.images: batch_images, self.labels:
                    batch_labels})
                loss += err
```

```python

            valid_psnr = []
            for idx in range(len(valid_images)):
                h, w, _ = valid_images[idx].shape
                valid_input_y = valid_images[idx][:, :, 0]
                valid_label_y = valid_labels[idx][:, :, 0]

                valid_input_y = valid_input_y.reshape([1, h, w, 1])
                valid_label_y = valid_label_y.reshape([1, h, w, 1])

                result = self.sess.run(self.result, feed_dict={self.images: valid_input_y, self.labels: valid_label_y})

                valid_label_y = crop_border(valid_label_y[0])

                if i == 0:
                        bicubic_psnr.append(psnr(valid_label_y, crop_border(valid_input_y[0])))
                valid_psnr.append(psnr(valid_label_y, result[0]))

            print('[*] Epoch: [{:d}], psnr: [bicubic: {:.2f}, srcnn: {:.2f}], loss: [{:.8f}]'.format(i+1, np.mean(bicubic_psnr), np.mean(valid_psnr), loss/batch_idxs))

            # Save model for every 50 epoch
            if (i+1) % 50 == 0:
                self.save(i+1, config)
        print('[*] Training done! Congrats :) ')


    def test(self, config):
        print('[*] SRCNN testing will be started! ')
        t = time.strftime('%Y-%m-%d-%H%M%S', time.localtime(time.time()))

        test_images, test_labels = prepare_data(config, is_valid=False)

        init = tf.global_variables_initializer()

        results = []
        bicubic_psnr = []
        test_psnr = []
```

```
        print('[*] Start testing !')

        self.sess.run(init)

        self.load(config)

        for idx in tqdm(range(len(test_images))):
            h, w, _ = test_images[idx].shape
            test_input_y = test_images[idx][:, :, 0]
            test_label_y = test_labels[idx][:, :, 0]

            test_input_cbcr = test_images[idx][:, :, 1:3]
            test_label_cbcr = test_labels[idx][:, :, 1:3]

            test_input_y = test_input_y.reshape([1, h, w, 1])
            test_label_y = test_label_y.reshape([1, h, w, 1])

            test_input_cbcr = test_input_cbcr.reshape([1, h, w, 2])
            test_label_cbcr = test_label_cbcr.reshape([1, h, w, 2])

            result = self.sess.run(self.result, feed_dict={self.images: test_input_y, self.labels: test_label_y})

            test_input_y = crop_border(test_input_y[0])
            test_label_y = crop_border(test_label_y[0])

            test_input_cbcr = crop_border(test_input_cbcr[0])
            test_label_cbcr = crop_border(test_label_cbcr[0])

            bicubic_psnr.append(psnr(test_label_y, test_input_y))
            test_psnr.append(psnr(test_label_y, result[0]))

            gt = concat_ycrcb(test_label_y, test_label_cbcr)
            bicubic = concat_ycrcb(test_input_y, test_input_cbcr)
            result = concat_ycrcb(result[0], test_input_cbcr)

            path = os.path.join(os.getcwd(), config.result_dir)
            path = os.path.join(path, t)
            if not os.path.exists(path):
                os.makedirs(path)

```

```python
            save_result(path, gt, bicubic, result, idx)

        print('[*] PSNR of ground truth and bicubic : {:.2f}'.format(np.mean(bicubic_psnr)))
        print('[*] PSNR of ground truth and SRCNN   : {:.2f}'.format(np.mean(test_psnr)))


    def save(self, epoch, config):
        model_name = 'srcnn'
        model_dir = 'SRCNN'
        path = os.path.join(config.checkpoint_path, model_dir)
        if not os.path.exists(path):
            os.makedirs(path)

        self.saver.save(self.sess, os.path.join(path, model_name), global_step=epoch)
        print('[*] Save checkpoint at {:d} epoch'.format(epoch))


    def load(self, config):
        if config.use_pretrained:
            model_dir = 'SRCNN_pretrained'
        else:
            model_dir = 'SRCNN'
        path = os.path.join(config.checkpoint_path, model_dir)
        ckpt_path = tf.train.latest_checkpoint(path)
        if ckpt_path:
            self.saver.restore(self.sess, ckpt_path)
            print('[*] Load checkpoint: {}'.format(ckpt_path))
        else:
            print('[*] No checkpoint to load ... ')
```

utils.py 程式碼如下所示。

```python
# import tensorflow as tf
import tensorflow
import tensorflow.compat.v1 as tf
import numpy as np
import math

from PIL import Image
```

```

from tqdm import tqdm

import os
import h5py

# FLAGS = tf.app.flags.FLAGS
FLAGS = tf.compat.v1.app.flags.FLAGS



# Read image
def imread(fname):
    return Image.open(fname)


# Save image
def imsave(image, path, fname):
    image = image * 255.

    image = Image.fromarray(image.astype('uint8'), mode='YCbCr')
    image = image.convert('RGB')

    return image.save(os.path.join(path, fname))


# Save ground truth image, bicubic interpolated image and srcnn image
def save_result(path, gt, bicubic, srcnn, i):
    imsave(gt, path, str(i)+ '_gt.png')
    imsave(bicubic, path, str(i) + '_bicubic.png')
    imsave(srcnn, path, str(i) + '_srcnn.png')


# Load sub-images of the dataset
def load_train_data():
    with h5py.File('train.h5', 'r') as f:
        images = np.array(f.get('data'))
        labels = np.array(f.get('label'))
    return images, labels


```

```python
# Return true if the h5 sub-images file is exists
def exist_train_data():
    return os.path.exists('train.h5')


def prepare_data(config, is_valid=False):
    if is_valid:
        dataset = config.valid_dataset
        path = os.path.join(config.test_dataset_path, dataset)
    else:
        dataset = config.test_dataset
        path = os.path.join(config.test_dataset_path, dataset)

    dir_path = os.path.join(os.getcwd(), path)
    path_gt = os.path.join(dir_path, 'gt')
    path_lr = os.path.join(dir_path, 'bicubic_{:d}x'.format(config.scale)
        )

    # fnames = ['baby_GT.bmp, bird_GT.bmp, ...']
    fnames = os.listdir(path_gt)

    inputs = []
    labels = []

    count = 0
    for fname in tqdm(fnames, desc='[*] Generating dataset ... '):
        count += 1

        _input = imread(os.path.join(path_lr, fname))
        _label = imread(os.path.join(path_gt, fname))

        _input = np.array(_input)
        _label = np.array(_label)

        inputs.append(_input / 255.)
        labels.append(_label / 255.)

    if is_valid:
        print('[*] Successfully prepared {:d} valid images !'.format(
            count))
    else:
```

```
        print('[*] Successfully prepared {:d} test images !'.format(count
           ))

    return inputs, labels


# Concatenate Y and CrCb channel
def concat_ycrcb(y, crcb):
    return np.concatenate((y, crcb), axis=2)


# Crop border of the image
def crop_border(image):
    padding = int((5+9+1-3)/2)
    if image.ndim == 3:
        h, w, _ = image.shape
    else:
        h, w = image.shape

    return image[padding:h-padding, padding:w-padding]


# Compute Peak Signal to Noise Ratio
# PSNR = 20 * log (MAXi / root(MSE))
def psnr(label, image, max_val=1.):
    h, w, _ = label.shape

    diff = image - label
    rmse = math.sqrt(np.mean(diff ** 2))
    if rmse == 0:
        return 100
    else:
        return 20 * math.log10(max_val / rmse)
```

下圖為測試結果與指令輸出整理。

(i) Bicubic (ii) GT (iii) SRCNN

Fig. 7. 測試結果

Epoch	PSNR-Bicubic	PSNR-SRCNN	Loss
10	28.39	28.21	0.00225721
20	28.39	28.49	0.00206320
30	28.39	28.78	0.00183421
40	28.39	28.89	0.00165385
50	28.39	28.85	0.00158986
60	28.39	28.86	0.00156327
70	28.39	28.88	0.00154177
80	28.39	28.88	0.00152562
90	28.39	28.89	0.00151489
100	28.39	28.89	0.00150848

5 Matlab H5 檔案

在前面測試的過程中頻繁出現 *.h5 的檔案，同時也有 *.m 的檔案，前者 *.h5 為層級資料格式（Hierarchical Data Format：HDF），目的是用於儲存和組織大量資料的一組檔案格式（HDF4，HDF5）。該檔案格式最初開發於美國國家超級計算應用中心 (National Center for Supercomputing Applications)，現在由非營利社團 HDF Group 進行支援，該組織的任務是確保 HDF5 技術的持續開發和儲存，並確保在 HDF 中資料的持續可存取性。該檔案格式可以存放資料集，而所謂的資料集則是是同質類型的多維陣列。而後者 *.m 則是 Matlab 的檔案格式，在此以 SRResNet 的 *.m 範例程式碼來進行產生。範例程式碼可以於 code 目錄下的 srresnet-matlab-m-to-h5-code 找到。

generate_train_srresnet.m 在 Matlab 加入路徑後，會導入 modcrop.m 和 store2hdf5.m 兩個檔案中的函式，同時並導入指定的影像訓練資料目錄進行訓練，最後產生 *.h5 資料。

generate_train_srresnet.m 程式碼如下所呈現。

```
clear;
close all;
%%folder = 'path/to/train/folder';
%%folder = '/Users/kancheng/py-work/matlab-py/data/train_data';
folder ='/Users/kancheng/py-work/matlab-py/data/train_data_demo';

%savepath = 'srresnet_x4.h5';
savepath ='srresnet_x4.h5';
%% scale factors
scale = 4;

size_label = 96;
size_input = size_label/scale;
stride = 48;

%% downsizing
downsizes = [1,0.7,0.5];

data = zeros(size_input, size_input, 3, 1);
label = zeros(size_label, size_label, 3, 1);

count = 0;
margin = 0;

%% generate data
filepaths = [];
filepaths = [filepaths; dir(fullfile(folder, '*.jpg'))];
filepaths = [filepaths; dir(fullfile(folder, '*.bmp'))];
filepaths = [filepaths; dir(fullfile(folder, '*.png'))];
```

```
length(filepaths)

for i = 1 : length(filepaths)
    for flip = 1: 3
        for degree = 1 : 4
            for downsize = 1 : length(downsizes)
                image = imread(fullfile(folder,filepaths(i).name));
                if flip == 1
                    image = flipdim(image ,1);
                end
                if flip == 2
                    image = flipdim(image ,2);
                end

                image = imrotate(image, 90 * (degree - 1));
                image = imresize(image,downsizes(downsize),'bicubic');

                if size(image,3)==3
                    %image = rgb2ycbcr(image);
                    image = im2double(image);
                    im_label = modcrop(image, scale);
                    [hei,wid, c] = size(im_label);

                    filepaths(i).name
                    for x = 1 + margain : stride : hei-size_label+1 - margain
                        for y = 1 + margain :stride : wid-size_label+1 - margain
                            subim_label = im_label(x : x+size_label-1, y : y+size_label-1, :);
                            subim_input = imresize(subim_label,1/scale,'bicubic');
                            % figure;
                            % imshow(subim_input);
                            % figure;
                            % imshow(subim_label);
                            count=count+1;
                            data(:, :, :, count) = subim_input;
                            label(:, :, :, count) = subim_label;
                        end
```

```
                    end
                end
            end
        end
    end
end

order = randperm(count);
data = data(:, :, :, order);
label = label(:, :, :, order);

%% writing to HDF5
chunksz = 64;
created_flag = false;
totalct = 0;

for batchno = 1:floor(count/chunksz)
    batchno
    last_read=(batchno-1)*chunksz;
    batchdata = data(:,:,:,last_read+1:last_read+chunksz);
    batchlabs = label(:,:,:,last_read+1:last_read+chunksz);
    startloc = struct('dat',[1,1,1,totalct+1], 'lab', [1,1,1,totalct+1]);
    curr_dat_sz = store2hdf5(savepath, batchdata, batchlabs, ~
       created_flag, startloc, chunksz);
    created_flag = true;
    totalct = curr_dat_sz(end);
end

h5disp(savepath);
```

modcrop.m 如下呈現。

```
function imgs = modcrop(imgs, modulo)
if size(imgs,3)==1
    sz = size(imgs);
    sz = sz - mod(sz, modulo);
    imgs = imgs(1:sz(1), 1:sz(2));
else
    tmpsz = size(imgs);
    sz = tmpsz(1:2);
    sz = sz - mod(sz, modulo);
    imgs = imgs(1:sz(1), 1:sz(2),:);
```

```
end
```

store2hdf5.m 如下呈現。

```
function [curr_dat_sz, curr_lab_sz] = store2hdf5(filename, data, labels, create, startloc, chunksz)
  % *data* is W*H*C*N matrix of images should be normalized (e.g. to lie between 0 and 1) beforehand
  % *label* is D*N matrix of labels (D labels per sample)
  % *create* [0/1] specifies whether to create file newly or to append to previously created file, useful to store information in batches when a dataset is too big to be held in memory  (default: 1)
  % *startloc* (point at which to start writing data). By default,
  % if create=1 (create mode), startloc.data=[1 1 1 1], and startloc.lab=[1 1];
  % if create=0 (append mode), startloc.data=[1 1 1 K+1], and startloc.lab = [1 K+1]; where K is the current number of samples stored in the HDF
  % chunksz (used only in create mode), specifies number of samples to be stored per chunk (see HDF5 documentation on chunking) for creating HDF5 files with unbounded maximum size - TLDR; higher chunk sizes allow faster read-write operations

  % verify that format is right
  dat_dims=size(data);
  lab_dims=size(labels);
  num_samples=dat_dims(end);

  assert(lab_dims(end)==num_samples, 'Number of samples should be matched between data and labels');

  if ~exist('create','var')
    create=true;
  end


  if create
    %fprintf('Creating dataset with %d samples\n', num_samples);
    if ~exist('chunksz', 'var')
      chunksz=1000;
    end
    if exist(filename, 'file')
```

```
      fprintf('Warning: replacing existing file %s \n', filename);
      delete(filename);
    end
    h5create(filename, '/data', [dat_dims(1:end-1) Inf], 'Datatype', 'single', 'ChunkSize', [dat_dims(1:end-1) chunksz]); % width, height, channels, number
    h5create(filename, '/label', [lab_dims(1:end-1) Inf], 'Datatype', 'single', 'ChunkSize', [lab_dims(1:end-1) chunksz]); % width, height, channels, number
    if ~exist('startloc','var')
      startloc.dat=[ones(1,length(dat_dims)-1), 1];
      startloc.lab=[ones(1,length(lab_dims)-1), 1];
    end
  else  % append mode
    if ~exist('startloc','var')
      info=h5info(filename);
      prev_dat_sz=info.Datasets(1).Dataspace.Size;
      prev_lab_sz=info.Datasets(2).Dataspace.Size;
      assert(prev_dat_sz(1:end-1)==dat_dims(1:end-1), 'Data dimensions must match existing dimensions in dataset');
      assert(prev_lab_sz(1:end-1)==lab_dims(1:end-1), 'Label dimensions must match existing dimensions in dataset');
      startloc.dat=[ones(1,length(dat_dims)-1), prev_dat_sz(end)+1];
      startloc.lab=[ones(1,length(lab_dims)-1), prev_lab_sz(end)+1];
    end
  end

  if ~isempty(data)
    h5write(filename, '/data', single(data), startloc.dat, size(data));
    h5write(filename, '/label', single(labels), startloc.lab, size(labels));
  end

  if nargout
    info=h5info(filename);
    curr_dat_sz=info.Datasets(1).Dataspace.Size;
    curr_lab_sz=info.Datasets(2).Dataspace.Size;
  end
end
```

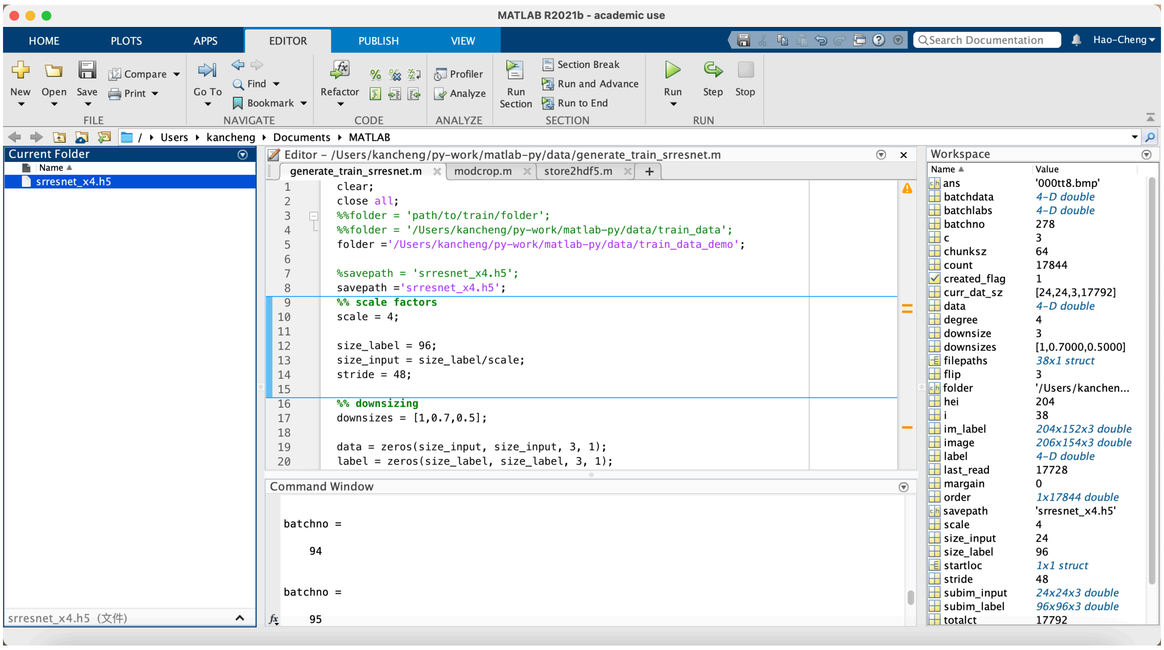

MATLAB R2021b - academic use
HOME
PLOTS
APPS
EDITOR
PUBLISH
VIEW
Search Documentation
Hao-Cheng
New
Open
Save
Compare
Print
FILE
Go To
Find
Bookmark
NAVIGATE
Refactor
CODE
Profiler
Analyze
ANALYZE
Run Section
Section Break
Run and Advance
Run to End
SECTION
Run
Step
Stop
RUN
/ Users kancheng Documents MATLAB
Current Folder
Name
srresnet_x4.h5
srresnet_x4.h5 (文件)
Editor - /Users/kancheng/py-work/matlab-py/data/generate_train_srresnet.m
generate_train_srresnet.m
modcrop.m
store2hdf5.m
clear;
close all;
%%folder = 'path/to/train/folder';
%%folder = '/Users/kancheng/py-work/matlab-py/data/train_data';
folder ='/Users/kancheng/py-work/matlab-py/data/train_data_demo';
%savepath = 'srresnet_x4.h5';
savepath ='srresnet_x4.h5';
%% scale factors
scale = 4;
size_label = 96;
size_input = size_label/scale;
stride = 48;
%% downsizing
downsizes = [1,0.7,0.5];
data = zeros(size_input, size_input, 3, 1);
label = zeros(size_label, size_label, 3, 1);
Command Window
batchno =
94
batchno =
95
Workspace
Name
Value
ans '000tt8.bmp'
batchdata 4-D double
batchlabs 4-D double
batchno 278
c 3
chunksz 64
count 17844
created_flag 1
curr_dat_sz [24,24,3,17792]
data 4-D double
degree 4
downsize 3
downsizes [1,0.7000,0.5000]
filepaths 38x1 struct
flip 3
folder '/Users/kanchen...
hei 204
i 38
im_label 204x152x3 double
image 206x154x3 double
label 4-D double
last_read 17728
margin 0
order 1x17844 double
savepath 'srresnet_x4.h5'
scale 4
size_input 24
size_label 96
startloc 1x1 struct
stride 48
subim_input 24x24x3 double
subim_label 96x96x3 double
totalct 17792

Fig. 8. Matlab

6 SR 算法整理

在此根據 Hongying Liu et al.[1] 將 SR 算法等重要的研究文獻整理，如下所示:

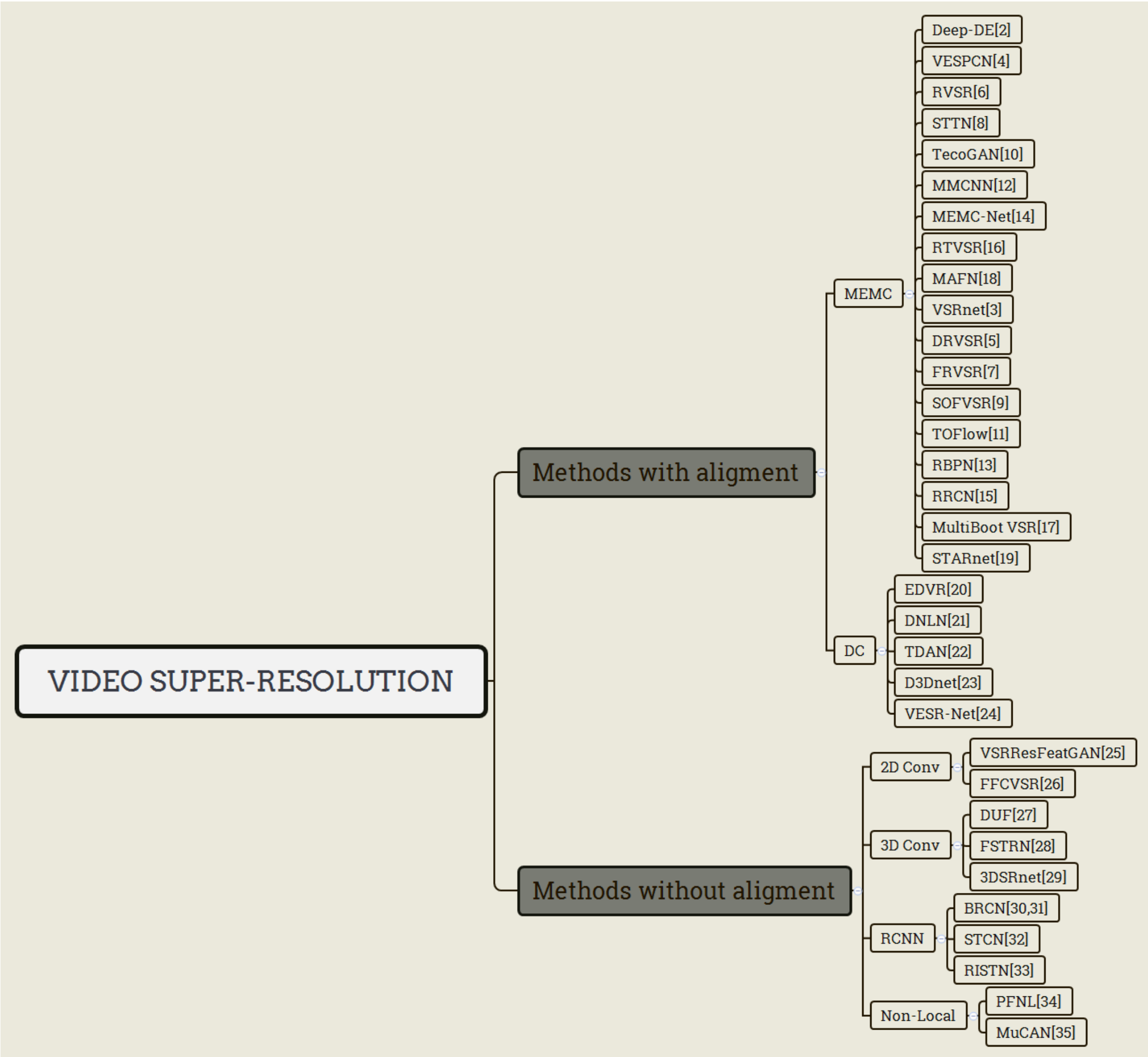


Fig. 9. SR 算法整理

從上面圖中可以看到 MEMC 代表運動估計和補償方法，DC 是可變形卷積方法，3D Conv 是 3D 卷積方法，RCNN 表示基於循環卷積神經網絡的方法。而下表則是近來 SR 算法與分類的整理，而該表也是根據 Hongying Liu et al.[1] 整理而成。

Method	Year	Synonym	Type
Deep-DE [2]	2015	Deep Draft-Ensemble Learning	MEMC
VSRnet [3]	2016	Video Super-Resolution with convolutional neural Networks	MEMC
VESPCN [4]	2017	Video Efficient Sub-pixel Convolutional Network	MEMC
DRVSR [5]	2017	Detail-Revealing deep Video Super-Resolution	MEMC
RVSR [6]	2017	Robust Video Super-Resolution	MEMC
FRVSR [7]	2018	Frame-Recurrent Video Super-Resolution	MEMC
STTN [8]	2018	Spatio-Temporal Transformer Network	MEMC
SOFVSR [9]	2018	Super-resolution Optical Flow for Video SuperResolution	MEMC
TecoGAN [10]	2018	Temporally coherent GAN	MEMC
TOFlow [11]	2019	video enhancement with Task-Oriented Flow	MEMC
MMCNN [12]	2019	Multi-Memory Convolutional Neural Network	MEMC
RBPN [13]	2019	Recurrent Back-Projection Network	MEMC
MEMC-Net [14]	2019	Motion Estimation and Motion Compensation Network	MEMC
RRCN [15]	2019	Residual Recurrent Convolutional Network	MEMC
RTVSR [16]	2019	Real-Time Video Super-Resolution	MEMC
MultiBoot VSR[17]	2019	Multi-stage multi-reference Bootstrapping for Video Super-Resolution	MEMC
MAFN [18]	2020	Motion-Adaptive Feedback Network	MEMC
STARnet [19]	2020	Space-Time-Aware multi-Resolution network	MEMC
EDVR [20]	2019	Enhanced Deformable convolutional networks for Video Restoration	DC
DNLN [21]	2019	Deformable Non-Local Network for Video Super-Resolution	DC
TDAN [22]	2020	Temporally-Deformable Alignment Network for Video Super-Resolution	DC
D3Dnet [23]	2020	Deformable 3D Convolution for Video SuperResolution	DC
VESR-Net [24]	2020	Video Enhancement and Super-Resolution Network	DC
VSRResFeatGAN [25]	2019	Video Super-Resolution with Residual Networks	2D Conv
FFCVSR [26]	2019	Frame and Feature-Context Video SuperResolution	2D Conv
DUF [27]	2018	video super-resolution network using Dynamic Upsampling Filters	3D Conv
FSTRN [28]	2019	Fast Spatio-Temporal Residual Network for Video Super-Resolution	3D Conv
3DSRnet [29]	2019	3D Super-Resolution Network	3D Conv
BRCN [30, 31]	2015/2018	video super-resolution via Bidirectional Recurrent Convolutional Networks	RCNN
STCN [32]	2017	Spatio-Temporal Convolutional Network for Video Super-Resolution	RCNN
RISTN [33]	2019	Residual Invertible Spatio-Temporal Network for Video Super-Resolution	RCNN
PFNL [34]	2019	Progressive Fusion network via exploiting NonLocal spatio-temporal correlations	Non-Local
MuCAN [35]	2020	Multi-Correspondence Aggregation Network for Video Super-Resolution	Non-Local

7 参考文獻

[1] Hongying Liu, Zhubo Ruan, Peng Zhao, Chao Dong, Fanhua Shang, Yuanyuan Liu, Linlin Yang, “Video Super Resolution Based on Deep Learning: A Comprehensive Survey”arXiv preprint arXiv:2007.12928, 2020.

[2] R. Liao, X. Tao, R. Li, Z. Ma, and J. Jia, “Video super-resolution via deep draft-ensemble learning,” in Proc IEEE Int. Conf. Comput. Vis., 2015, pp. 531–539.

[3] A. Kappeler, S. Yoo, Q. Dai, and A. K. Katsaggelos, “Video super-resolution with convolutional neural networks,” IEEE Trans. Comput. Imaging, vol. 2, no. 2, pp. 109–122, June 2016.

[4] J. Caballero, C. Ledig, A. Aitken, A. Acosta, J. Totz, Z. Wang, and W. Shi, “Real-time video super-resolution with spatio-temporal networks and motion compensation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2017, pp. 2848–2857.

[5] X. Tao, H. Gao, R. Liao, J. Wang, and J. Jia, “Detailrevealing deep video super-resolution,” in Proc IEEE Int. Conf. Comput. Vis., 2017, pp. 4482–4490.

[6] D. Liu, Z. Wang, Y. Fan, X. Liu, Z. Wang, S. Chang, and T. Huang, “Robust video super-resolution with learned temporal dynamics,” in Proc IEEE Int. Conf. Comput. Vis., 2017, pp. 2526–2534.

[7] M. S. M. Sajjadi, R. Vemulapalli, and M. Brown, “Frame-recurrent video super-resolution,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2018, pp. 6626–6634.

[8] T. H. Kim, M. S. M. Sajjadi, M. Hirsch, and B. Scholkopf, “Spatio-temporal transformer network for video restoration,” in Comput. Vis. - ECCV, 2018, pp. 111–127.

[9] L. Wang, Y. Guo, Z. Lin, X. Deng, and W. An, “Learning for video super-resolution through HR optical flow estimation,” in Proc. Asian Conf. Comput. Vis., 2019, pp. 514–529.

[10] M. Chu, Y. Xie, J. Mayer, L. Leal-Taixe, and N. Thuerey, “Learning Temporal Coherence via Self-Supervision for GAN-based Video Generation,” arXiv e-prints, 2018.

[11] T. Xue, B. Chen, J. Wu, D. Wei, and W. T. Freeman, “Video enhancement with task-oriented flow,” Int. J. Comput. Vis., vol. 127, no. 8, pp. 1106–1125, Aug 2019.

[12] Z. Wang, P. Yi, K. Jiang, J. Jiang, Z. Han, T. Lu, and J. Ma, “Multi-memory convolutional neural network for video super-resolution,” IEEE Trans. Image Process., vol. 28, no. 5, pp. 2530–2544, May 2019.

[13] M. Haris, G. Shakhnarovich, and N. Ukita, “Recurrent back-projection network for video super-resolution,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2019, pp. 3892–3901.

[14] W. Bao, W. Lai, X. Zhang, Z. Gao, and M. Yang, “MEMC-Net: Motion estimation and motion compensation driven neural network for video interpolation and enhancement,” IEEE Trans. Pattern Anal. Mach. Intell., 2019.

[15] D. Li, Y. Liu, and Z. Wang, “Video super-resolution using non-simultaneous fully recurrent convolutional network,” IEEE Trans. Image Process., vol. 28, no. 3, pp. 1342–1355, March 2019.

[16] B. Bare, B. Yan, C. Ma, and K. Li, “Real-time video super-resolution via motion convolution kernel estimation,” Neurocomputing, vol. 367, pp. 236–245, 2019.

[17] R. Kalarot and F. Porikli, “MultiBoot VSR: Multistage multi-reference bootstrapping for video super-resolution,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops, 2019, pp. 2060–2069.

[18] J. Xin, N. Wang, J. Li, X. Gao, and Z. Li, “Video face super-resolution with motion-adaptive feedback cell.” in Proc. AAAI Conf. Artif. Intell., 2020, pp.12 468–12 475.

[19] M. Haris, G. Shakhnarovich, and N. Ukita, “Space-time-aware multi-resolution video enhancement,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2020, pp. 2859–2868.

[20] X. Wang, K. C. K. Chan, K. Yu, C. Dong, and C. C. Loy, “EDVR: Video restoration with enhanced deformable convolutional networks,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops, 2019, pp. 1954–1963.

[21] H. Wang, D. Su, C. Liu, L. Jin, X. Sun, and X. Peng, “Deformable non-local network for video super-resolution,” IEEE Access, vol. 7, pp. 177 734–177 744, 2019.

[22] Y. Tian, Y. Zhang, Y. Fu, and C. Xu, “TDAN: Temporally-deformable alignment network for video super-resolution,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2020, pp. 3360–3369.

[23] X. Ying, L. Wang, Y. Wang, W. Sheng, W. An, and Y. Guo, “Deformable 3d convolution for video super-resolution,” arXiv preprint arXiv:2004.02803, 2020.

[24] J. Chen, X. Tan, C. Shan, S. Liu, and Z. Chen, “Vesrnet: The winning solution to youku video enhancement and super-resolution challenge,” arXiv preprint arXiv:2003.02115, 2020.

[25] A. Lucas, S. LApez-Tapia, R. Molina, and A. K. Katsaggelos, “Generative adversarial networks and perceptual losses for video super-resolution,” IEEE Trans. Image Process., vol. 28, no. 7, pp. 3312–3327, July 2019.

[26] B. Yan, C. Lin, and W. Tan, “Frame and featurecontext video super-resolution,” in Proc. AAAI Conf. Artif. Intell., 2019, pp. 5597–5604.

[27] Y. Jo, S. W. Oh, J. Kang, and S. J. Kim, “Deep video super-resolution network using dynamic upsampling filters without explicit motion compensation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2018, pp. 3224–3232.

[28] S. Li, F. He, B. Du, L. Zhang, Y. Xu, and D. Tao, “Fast spatio-temporal residual network for video super-resolution,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2019, pp. 10 522–10 531.

[29] S. Y. Kim, J. Lim, T. Na, and M. Kim, “Video superresolution based on 3d-cnns with consideration of scene change,” in Proc. IEEE Int. Conf. Image Process., 2019, pp. 2831–2835.

[30] Y. Huang, W. Wang, and L. Wang, “Bidirectional recurrent convolutional networks for multi-frame super-resolution,” in Advances in Neural Information Processing Systems, 2015, pp. 235–243.

[31] Y. Huang, W. Wang, and L. Wang, “Video superresolution via bidirectional recurrent convolutional networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 40, no. 4, pp. 1015–1028, April 2018.

[32] J. Guo and H. Chao, “Building an end-to-end spatial-temporal convolutional network for video super-resolution,” in Proc. AAAI Conf. Artif. Intell., 2017, pp. 4053–4060.

[33] X. Zhu, Z. Li, X. Zhang, C. Li, Y. Liu, and Z. Xue, “Residual invertible spatio-temporal network for video super-resolution,” in Proc. AAAI Conf. Artif. Intell., 2019, pp. 5981–5988.

[34] P. Yi, Z. Wang, K. Jiang, J. Jiang, and J. Ma, “Progressive fusion video super-resolution network via exploiting non-local spatio-temporal correlations,” in Proc IEEE Int. Conf. Comput. Vis., 2019, pp. 3106–3115.

[35] W. Li, X. Tao, T. Guo, L. Qi, J. Lu, and J. Jia, “Mucan: Multi-correspondence aggregation network for video super-resolution,” arXiv preprint arXiv:2007.11803, 2020.