

Configuration Manual

M.Sc. Research Project
M.Sc. in Data Analytics

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Configuration Manual

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Research Project

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1 Introduction

The configuration manual provides a comprehensive set of steps to follow in order to replicate the research and verify the findings of the research. The manual is divided into sections that provide specific steps required for each component of the research.

2 System Configuration

Following are the minimum system requirements required for the research.

Operating System	Windows 10 or higher
RAM	16 GB
Minimum Hard Disk Space	128 GB
Processor	Intel 11 Gen, i5 or higher
GPU	Required for faster training of the model.

3 Integrated Development Environment

The following software (Integrated Development Environments) are required:

1. Anaconda Distribution Package: required for running .ipynb notebooks. <https://www.anaconda.com/products/distribution>
2. Python 3.9.7: the programming language. <https://www.python.org/downloads/release/python-397/>
3. Notepad++: for running .py files. <https://notepad-plus-plus.org/downloads/>

4 Python Libraries

The python libraries are the packages required to execute and create prediction models. To install the libraries open the Anaconda prompt and use the following command: **pip install library-name == library-version**

Following is the list of the libraries to install:

- colorama==0.4.4
- cuda-python==11.8.1
- keras==2.9.0
- matplotlib==3.4.3
- numpy==1.20.3
- opencv-python==4.5.5.64
- pandas==1.3.4
- Pillow==8.4.0
- scikit-learn==1.1.2
- scipy==1.7.1
- seaborn==0.11.2
- tensorflow==2.9.1
- torch==1.13.0
- torchvision==0.14.0
- tqdm==4.62.3

5 Dataset

The dataset for the research can be downloaded following the following url: <https://www.kaggle.com/datasets/tthien/shanghaitech>
Create a directory "CrowdDetection". Create a subdirectory "Data" and place the part_A and part_B folders of the Shanghai dataset in this directory.

6 Code File Names

The research contains the following code files:

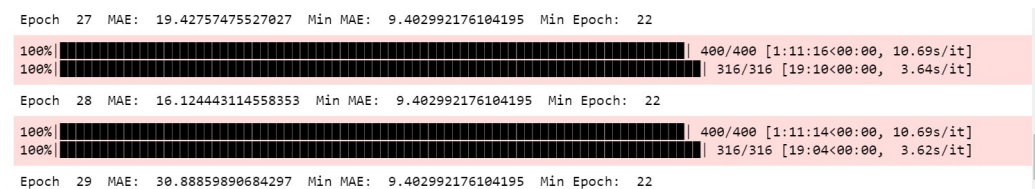
1. **generateDensityMapsPartA.ipynb** converts part_A image data to NumPy files containing density map information.
2. **generateDensityMapsPartB.ipynb** converts part_B image data to NumPy files containing density map information.
3. **utils.py** contains parameters for normalization of image data.
4. **config.py** contains configuration data for the crowd-detection model like the number of epochs, and batch size.
5. **dataset.py** python file that creates a data loader for the crowd-density detection model
6. **model.py** python file that creates the crowd-detection model.
7. **train.ipynb** the notebook to train the crowd-detection model on the crowd data.
8. **01.Get_Density_Map.ipynb** converts image data to density map image.
9. **02.Convert_Density_Map_To_Grid_Graph.ipynb** converts density map image to grid graph representation.
10. **03.A-Star Path Finding Algorithm.ipynb** finds the optimal path using A* path-finding algorithm.
11. **04.Simulation_A_Star.ipynb** verifies the A* path against the path provided by greedy path-finding algorithm.
12. **05.GraphColoring.ipynb** provides different colors for the flight gates

7 Crowd-Detection Model

To create the crowd detection model, we need to run the mentioned files in a sequence. The **root directory** is the "CrowdDetection" directory we created in the Dataset section. Copy all the code files inside the root directory. The sequence is defined in the below section.

7.1 Data preparation

1. Navigate to the "Data" folder. Place *generateDensityMapsPartA.ipynb* file into part_A folder and *generateDensityMapsPartB.ipynb* file into the part_B folder inside the data folder. Run these two files in Jupyter and wait until completion as in the figure below.



7.2 dataset.py

This python file creates a data loader used to train and test images. The phase is used to change the folder for training data. By default it is set to *train_data* folder inside *part_B* folder of Data folder.

```
14 class CrowdDataset(torch.utils.data.Dataset):
15     ...
16     CrowdDataset
17     ...
18
19     def __init__(self, root, phase, main_transform=None, img_transform=None, dmap_transform=None):
20         ...
21         root: the root path of dataset.
22         phase: train or test.
23         main_transform: transforms on both image and density map.
24         img_transform: transforms on image.
25         dmap_transform: transforms on densitymap.
26         ...
27         self.img_path = os.path.join(root, phase+'_data', 'images')
28         # print(self.img_path)
29         self.dmap_path = os.path.join(root, phase+'_data', 'densitymaps')
30         # print(self.dmap_path)
31         self.data_files = [filename for filename in os.listdir(self.img_path)
32                             if os.path.isfile(os.path.join(self.img_path, filename))]
33         self.main_transform = main_transform
34         self.img_transform = img_transform
35         self.dmap_transform = dmap_transform
36     ...
```

The data loader method reads images from the specified folder and creates a tensor

of each image. Data augmentation is carried out by calling `RandomHorizontalFlip` which is controlled by `use_flip` flag, and `PairedCrop` functions as shown in the figure.

```

64 def create_train_dataloader(root, use_flip, batch_size):
65     """
66     Create train dataloader.
67     root: the dataset root.
68     use_flip: True or false.
69     batch size: the batch size.
70     """
71     main_trans_list = []
72     if use_flip:
73         main_trans_list.append(RandomHorizontalFlip())
74     main_trans_list.append(PairedCrop())
75     main_trans = Compose(main_trans_list)
76     img_trans = Compose([ToTensor(), Normalize(mean=[0.5,0.5,0.5],std=[0.225,0.225,0.225])])
77     dmap_trans = ToTensor()
78     dataset = CrowdDataset(root=root, phase='train', main_transform=main_trans,
79                           img_transform=img_trans,dmap_transform=dmap_trans)
80     dataloader = torch.utils.data.DataLoader(dataset,batch_size=batch_size,shuffle=True)
81     return dataloader

```

7.3 model.py

The `model.py` actually creates the CSRNet crowd-density detection model. The `frontend_feat` in `__init__()` method of CSRNet class is the list of size of input layers in the frontend layers of the model. Similarly, `backend_feat` is the list of the size of input layers in the backend layers of the model.

```

8 class CSRNet(nn.Module):
9     def __init__(self, load_weights=False):
10         super(CSRNet, self).__init__()
11         self.frontend_feat = [64, 64, 'M', 128, 128,
12                             'M', 256, 256, 256, 'M', 512, 512, 512]
13         self.backend_feat = [512, 512, 512, 256, 128, 64]
14         self.frontend = make_layers(self.frontend_feat)
15         self.backend = make_layers(
16             self.backend_feat, in_channels=512, dilation=True)
17         self.output_layer = nn.Conv2d(64, 1, kernel_size=1)
18         if not load_weights:
19             mod = models.vgg16(pretrained=True)
20             self._initialize_weights()
21             fsd = collections.OrderedDict()
22             # 10 convlution *(weight, bias) = 20 parameters
23             # state_dict (dict) - a dict containing parameters and persistent buffers.
24             for i in range(len(self.frontend.state_dict().items())):
25                 temp_key = list(self.frontend.state_dict().items())[i][0]
26                 fsd[temp_key] = list(mod.state_dict().items())[i][1]
27             # Load_state_dict: Copies parameters and buffers from state_dict into this module and its descendants.
28             self.frontend.load_state_dict(fsd)
29

```

The `make_layer` function creates the sequential CSRNet layers. In an 'M' is encountered in the list of layers, a max-pooling layer is added instead of a convolutional layer. If `batch_norm` is set to true Batch Normalization layer is added to the model. If `dilation` is set to True, a dilation layer of size 2 is added to the model,

else dilation layer of size 1 is added as shown in the figure.

```
48 def make_layers(cfg, in_channels=3, batch_norm=False, dilation=False):
49     if dilation:
50         d_rate = 2
51     else:
52         d_rate = 1
53     layers = []
54     for v in cfg:
55         if v == 'M':
56             layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
57         else:
58             conv2d = nn.Conv2d(in_channels, v, kernel_size=3,
59                               padding=d_rate, dilation=d_rate)
60             if batch_norm:
61                 layers += [conv2d, nn.BatchNorm2d(v), nn.ReLU(inplace=True)]
62             else:
63                 layers += [conv2d, nn.ReLU(inplace=True)]
64             in_channels = v
65     return nn.Sequential(*layers)
```

7.4 Training Phase

1. Now initialize the parameters in config.py. The parameters inside the `__init__` method can be adjusted to control the training phase.

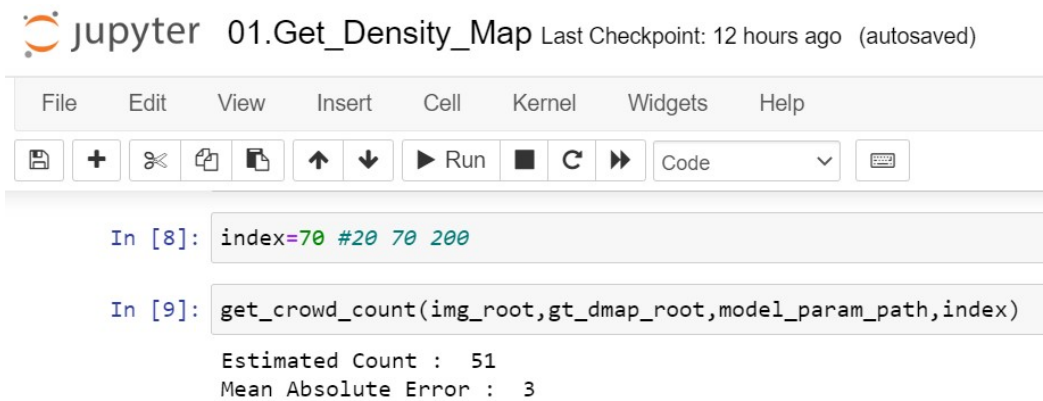
```
~
7 class Config():
8     '''
9     Config class
10    '''
11    def __init__(self):
12        current_directory = os.getcwd()
13        dataset_path = os.path.join(current_directory, "Data", "part_B")
14        self.dataset_root = dataset_path
15        self.device = torch.device('cuda') if torch.cuda.is_available() else torch.device('cpu')
16        self.lr = 1e-5 # Learning rate
17        self.batch_size = 1 # batch size
18        self.epochs = 30 # epochs
19        self.checkpoints = './checkpoints' # checkpoints dir
20        self.writer = SummaryWriter() # tensorboard writer
21
22        self.__mkdir(self.checkpoints)
```

2. Run train.py In research, we are using 30 epochs(0-29) so the model stops training at epoch 29 as in the figure below.


```
Epoch 27 MAE: 19.42757475527027 Min MAE: 9.402992176104195 Min Epoch: 22
100%|██████████████████████████████████████████████████████████████████████████████| 400/400 [1:11:16<00:00, 10.69s/it]
100%|██████████████████████████████████████████████████████████████████████████████| 316/316 [19:10<00:00, 3.64s/it]
Epoch 28 MAE: 16.124443114558353 Min MAE: 9.402992176104195 Min Epoch: 22
100%|██████████████████████████████████████████████████████████████████████████████| 400/400 [1:11:14<00:00, 10.69s/it]
100%|██████████████████████████████████████████████████████████████████████████████| 316/316 [19:04<00:00, 3.62s/it]
Epoch 29 MAE: 30.88859890684297 Min MAE: 9.402992176104195 Min Epoch: 22
```

7.5 Predict crowd Density

Run the *01.Get_Density_Map.ipynb* file. To get the density map of an image, set the index to the index of the image inside the text_data folder. In the research, the **test images** are kept inside *CrowdDetection/Data/part_B/test_data/images* folder. The index can be set in cell 8 of the notebook as shown in the figure.



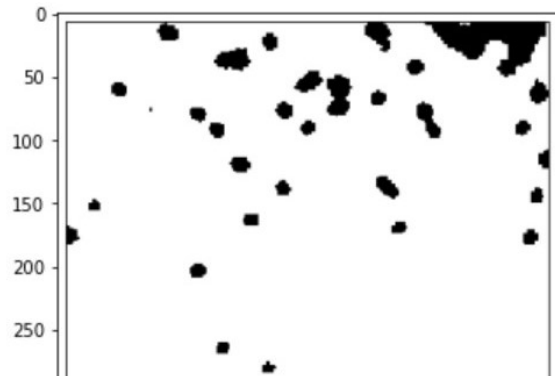
```
jupyter 01.Get_Density_Map Last Checkpoint: 12 hours ago (autosaved)
File Edit View Insert Cell Kernel Widgets Help
[Save] [New] [Close] [Copy] [Paste] [Up] [Down] [Run] [Stop] [Refresh] [Next] Code [Keyboard]

In [8]: index=70 #20 70 200

In [9]: get_crowd_count(img_root,gt_dmap_root,model_param_path,index)
Estimated Count : 51
Mean Absolute Error : 3
```

The output is the density map image of the given image as shown in the figure.

```
Out[14]: <matplotlib.image.AxesImage at 0x1f7007d1550>
```



8 OpenCV method to convert density map image to grid graph representation

Run *02.Convert_Density_Map_To_Grid_Graph.ipynb* file. The image is divided into regions using a loop. A threshold method gets the solid color for the image and an average function calculates the average intensity of the color. If the intensity is zero, the region of the image is an obstacle in the grid. The data is written into a text file. An '\$' sign denotes an obstacle and a '-' sign denotes a path in the text file.

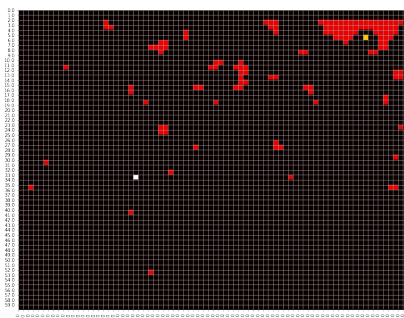
```
jupyter 02.Convert_Density_Map_To_Grid_Graph Last Checkpoint: a few seconds ago (autosaved)
```

```
File Edit View Insert Cell Kernel Widgets Help
```

```
Run Code
```

```
In [5]: list_for_astar = []
f = open("demofile2.txt", "w")
for y in np.linspace(0,thresh1.shape[0],61):
    if y == 300:
        break
    inner_list = []
    for x in np.linspace(0,thresh1.shape[1],80):
        f = open("demofile2.txt", "a")
        if x==395.0:
            break
        roi = thresh1[int(y):int(y)+5,int(x):int(x)+5]
        avg_color_per_row = np.average(roi, axis=0)
        avg_color = np.average(avg_color_per_row, axis=0)
        # print(avg_color)
        if avg_color==0:
            # print("Black Obstacle")
            inner_list.append(" $ ")
            f.write(" $ ")
        else:
            # print("White Path")
            inner_list.append(" - ")
            f.write(" - ")
```

The output of the file is the grid visual in the file.



9 A* path-finding algorithm

Run *03.A-Star Path Finding Algorithm.ipynb* file. The Node class creates an object that contains information about each square in the grid. The children function considers the square in all four direction. It is the next square that can be used to move. A square is a possible path only if it is not an obstacle of '\$' in the text file created in the last step.

```
In [2]: class Node:
        def __init__(self,value,point):
            self.value = value
            self.point = point
            self.parent = None
            self.H = 0
            self.G = 0
        def move_cost(self,other):
            return 0 if self.value == '-' else 1
```

Mention the cost in the report

```
In [3]: def children(point,grid):
        x,y = point.point
        possible_links=[[x-1, y],[x,y - 1],[x,y + 1],[x+1,y]]
        links = [grid[d[0]][d[1]] for d in possible_links if -1<d[0]<60 if -1<d[1]<79]
        return [link for link in links if link.value != '$']
```

The aStar function finds the path using two sets that contain visited and non-visited nodes for the path. Two cost functions namely, G-cost and H-cost are used. These are o.G and o.H in the code.

```
In [5]: def aStar(start, goal, grid):
        #The open and closed sets
        openset = set()
        closedset = set()
        #Current point is the starting point
        current = start
        #Add the starting point to the open set
        openset.add(current)

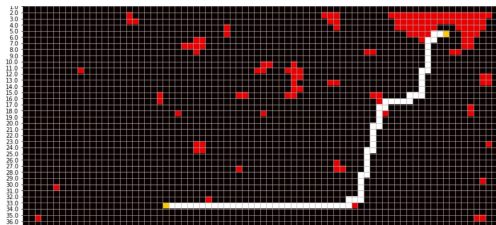
        #While the open set is not empty
        while openset:
            #Find the item in the open set with the Lowest G + H score
            current = min(openset, key=lambda o:o.G + o.H)
            #If it is the item we want, retrace the path and return it
            if current == goal:
                path = []
                while current.parent:
                    path.append(current)
                    current = current.parent
                path.append(current)
                return path[::-1]
```

Provide the coordinates for the start location and destination location in the grid graph for which you want to find the path.

```
In [10]: start_pos=input("Enter start position in format x<space>y:") #(17 23) (5 69) (20 45)
Enter start position in format x<space>y:5 69

In [11]: dest_pos=input("Enter destination position in format x<space>y:") #(7 61) (33 23) (0 15)
Enter destination position in format x<space>y:33 23
```

The output of the notebook is the A* path as shown in the figure.



10 Simulation

Run *04.Simulation_A_Star.ipynb* file. Set the start and destination location for the simulation.

```
In [5]: start_pos=input("Enter start position in format x<space>y:") #(17 23) (5 69) (20 45)
Enter start position in format x<space>y:5 69

In [6]: dest_pos=input("Enter destination position in format x<space>y:") #(7 61) (33 23) (0 15)
Enter destination position in format x<space>y:33 23
```

We implement an algorithm to find the greedy path. Notice here only G-cost is used which is the Manhattan distance of the square currently considered for the path from the start location.

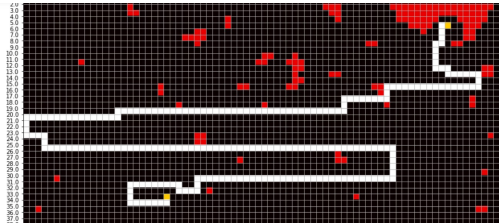
```
In [17]: def findPath(start, goal, grid):
#The open and closed sets
openset = set()
closedset = set()
#Current point is the starting point
current = start
#Add the starting point to the open set
openset.add(current)
```

Next, we check if the path returned by the greedy algorithm does not cross any crowd-density areas or obstacles in the grid graph. The red squares are the obstacles in the grid graph.

Check if path reaches any crowd density area


```
In [21]: normalpath = dict()
i=1
for node in path:
    x, y = node.point
    normalpath[i] = [x,y]
    i+=1
normalpath
```

The output of the notebook is the plot for the path returned by the greedy algorithm.



11 Graph Coloring Algorithm

Run *05.GraphColoring.ipynb* file. Take the image of the terminal map and convert it to the adjacency matrix using the list of lists. The row and columns of the matrix are the names of the boarding gates in the node list.



```
In [3]: G = [[ 0, 1, 0, 0, 0, 1],
[ 1, 0, 1, 0, 0, 0],
[ 0, 1, 0, 1, 0, 0],
[ 0, 0, 1, 0, 1, 0],
[ 0, 0, 0, 1, 0, 1],
[ 1, 0, 0, 0, 1, 0]]

# initiate the name of node.
node = ['307A', '307', '306', '303', '302', '301']
```

After completion of the execution of the code, the output will be as shown in the figure.

```
Boardig Station - 301 : Red
Boardig Station - 302 : Blue
Boardig Station - 303 : Red
Boardig Station - 306 : Blue
Boardig Station - 307 : Red
Boardig Station - 307A : Blue
```