CSC420 Project Report

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December 2019

1 Introduction

In this project, we are going to perform analysis on videos, in particular, news broadcast. There are various tasks associated with the video analysis, such as shot detection, feature detection and recognition, and feature tracking between frames. Video processing has been a popular area in computer vision for a long time. In the project, we are going to employ novel ideas from the past few years to complete our analysis.

2 Shot Detection

Shot detection is crucial in video processing, it is a useful helper for other computer vision operations like face detection in consecutive frames[10]. I will perform three shot detection algorithms in 2.1 on the given video clips [5].

2.1 Method

The first two algorithms: Average Intensity Measurement 2.1.2 and Color Histogram Comparison 2.1.3, are very widely used in shot detection. They in general compares the color distribution of two images, which is robust to camera motion. The third method 2.1.4 is a relatively novel measurement, instead of collecting pixel color information, it focuses on object features.

Figure 1: case where traditional color histogram doesn't work in shot detection

2.1.1 Adaptive Thresholding

Before describing the details of the methods, I would talk about out threshold policy. In this project, the threshold policy we choose is called Adaptive Thresholding [14]. There are two hyperparameters in this thresholding, W denotes the window size and by default is an odd integer. T_c is a constant. For each dissimilarity score at time slot t, the threshold is

$$m_t = max(\mu_{left}+T_c\sqrt{\sigma_{left}}, \mu_{right}+T_c\sqrt{\sigma_{right}})$$

$\mu_{left}, \sigma_{left}$ is calculated from the dissimilarity values within interval $[d-W/2, d)$, and the similar manner for $\mu_{right}, \sigma_{right}$.

2.1.2 Mean Intensity Measurement (MIM)

This method is described briefly in [13], which computes the average intensity of each image channel, and sum the difference over all channels with the values of the next frame.

2.1.3 Color Histogram Comparison (CHC)

The traditional color histogram described in [13] takes intensity values at gray-scale, and calcutes the entire image intensities into one histogram. While we think this may not be ro-

Figure 2: the red box moves between frames

bust, Figure 1 is the case. If we take color histogram of these two images, the difference would zero. Our method slightly changes the traditional one. We first take color histogram of all three channels. Instead of taking the entire image size as the input, we make a small patch with size 16 to gather color information.

2.1.4 Edge Change Ratio (ECR)

The edge change ratio [11] is a method focuses more on the feature information within the image. Figure 2 shows a case that a box moves between frames but within a certain boundary. ECR tracks how edge features move between frames. This needs pre-processing on two frames.

Implementation

- We first calculate edge features (our implement applies canny edge with $\sigma = 5$) of both images, denoting both the image I_t, I_{t+1}, and processed canny edges C_t, C_{t+1}. Here we used OpenCV Canny Edge Detection functons.[2]

- Then apply dilation on both edge feature D_t^-, D_{t+1}^-, then we calculate the inverse

$$D_t = 1 - D_t^-$$

$$D_{t+1} = 1 - D_{t+1}^-$$

- Take binary operations between C_t, D_{t+1} and C_{t+1}, Dt. A binary operation is defined as $binary(A, B) = A * B$ when A, B only have values zero and one.

$$EC_{out} = \frac{binary(C_t, D_{t+1})}{Ct}$$

$$EC_{in} = \frac{binary(C_{t+1}, D_t)}{Ct + 1}$$

- The final edge change ratio is

$$ECR = max(EC_{in}, EC_{out})$$

2.2 Evaluation

[R:Recall, P:Precision, F1: F Score]
[C:Correct, M:Missed, F:False]

Clip	C	M	F	R	P	F1
#clip 1	1	0	2	1.00	0.33	0.50
#clip 2	8	0	2	1.00	0.80	0.89
#clip 3	4	2	9	0.67	0.40	0.50

Table 1: metrics of *Mean Intensity Measurement* over three clips

Clip	C	M	F	R	P	F1
#clip 1	1	0	2	1.00	0.33	0.50
#clip 2	8	0	7	1.00	0.53	0.70
#clip 3	4	2	8	0.67	0.33	0.44

Table 2: metrics of *Color Histogram Comparison* over three clips

Clip	C	M	F	R	P	F1
#clip 1	1	0	0	1.00	1.00	1.00
#clip 2	6	2	0	0.75	1.00	0.86
#clip 3	5	1	3	0.83	0.62	0.71

Table 3: metrics of *Edge Change Ratio* over three clips

The graph in Figure 3 4 5 shows the performance of three measurements respectively. The yellow vertical spans are the true video shot detections, where those thin lines indicate the hard cuts and wide spans indicate dissolve transitions. We also have the following tables 1 2 3 show the metrics of the three algorithm. The mathematical expressions for Recall, Precision and F measure (F1) [9] are

$$Recall = \frac{Correct}{Correct + Missed}$$

$$Precision = \frac{Correct}{Correct + False}$$

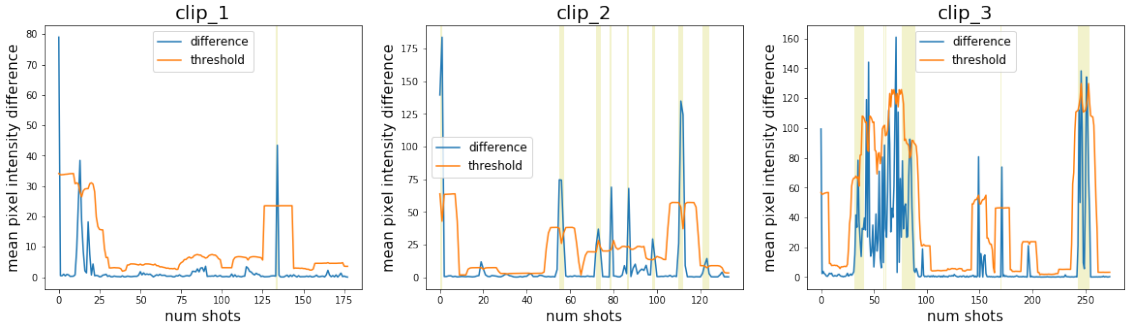

Figure 3: performance of Mean Intensity Measurement

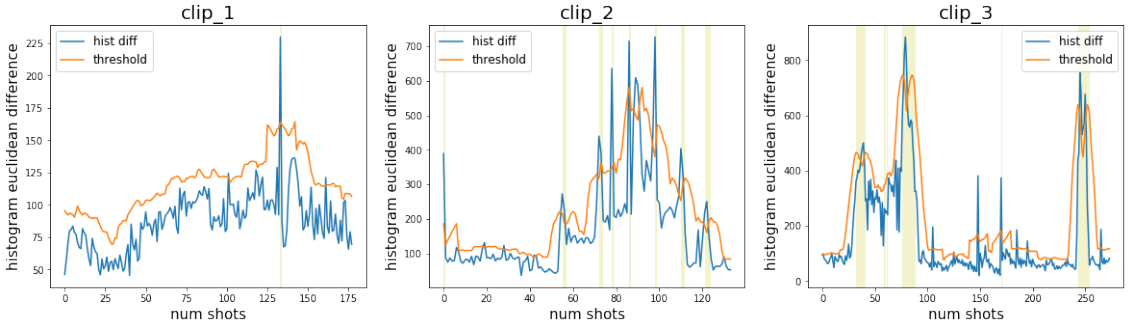

Figure 4: performance of Color Histogram Comparison

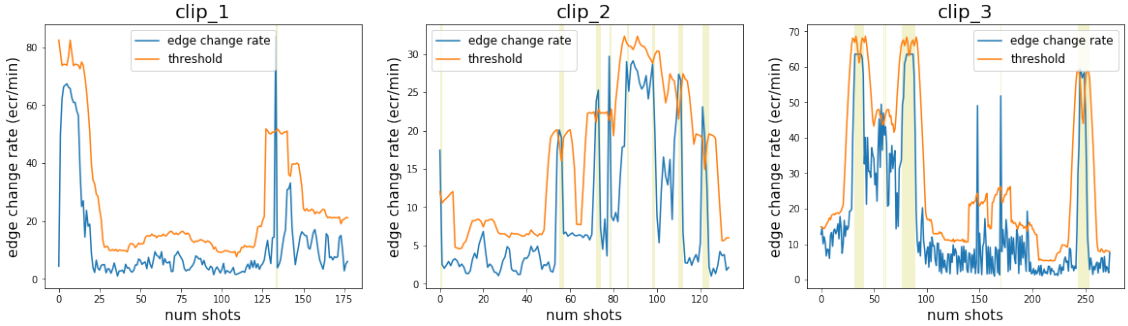

Figure 5: performance of Edge Change Ratio

$$F1 = \frac{2 \times Recall \times Precision}{Recall + Precision}$$

Intensity based algorithms tend to have a higher Recall and low Precision, since the given video clips[5] generally have frequently intensity changes, the algorithms capture both correct shot boundaries and intensity noise. On the other hand, the feature based algorithm (ECR) generally out performs the other two algorithms. Observe that the worst performance of the three clips[5] is the clip 3. This is because a rapid changing comic scenes (Marvel comic), the ECR is not robust to video clips that have low sampling rate, since in this case the object has a larget movement gap which causes the False detections.

3 Feature Detection

Feature detection field has been rapidly improved as the Deep Learning concept came out. Some deep learning algorithms now have extraordinary performances. However, there are still some widely used techniques that are non deep learning based which also have good performances. For face detection, we are going to use Haar Cascade Classifier[12], and for logo detection, we adopt a method that learnt from

Figure 6: missed face detection

lecture materials.

3.1 Face Detection

We uses Haar Cascade Classifier[12] as our face detector. The algorithm first collects a large number of features, we need to figure out which features among all of these best determine a face. And this is done by using Adaboost, a collection of weak learner. All the features are stacked together with different amount, from less to more, grouped into the classifier. The algorithm is also fast at real time because of the Cascade concept, it immediately discard a sliding window in detecting when it fails at any position inside the classifier. Though in terms of the performance, CNN is better, but it is more efficient in training and has lighter model. So for simple task such as face detection, Haar Cascade has always been a good choice.

3.1.1 Face Detection Results

From Table 4, we can see that the Haar Cascade Classifier has better Precison than Recall. This is due to the Cascade property discussed previously. In contrast, the performance in the first two clips is better than the last one, especially for Recall measurement. This is because the angle that people facing at in clips 3 is not towards the camera like in Fig 6. So the Haar feature filters are not able to apply on these case variations. Even though in general people has a common front face feature, the style on each left or right may vary. Unlike convolutional neural networks, which is of high freedom to perform optimal kernels (as weights to train), Haar features are manually determined, thus with a tighter limitation.

[R:Recall, P:Precision, F1: F Score]
[C:Correct, M:Missed, F:False]

Clip	C	M	F	R	P	F1
#clip 1	253	45	10	0.85	0.96	0.90
#clip 2	373	73	4	0.84	0.99	0.91
#clip 3	329	165	12	0.67	0.96	0.78

Table 4: metrics of *Haar Cascade Classifier* over three clips

3.2 Logo Detection

The method for Logo detection we used is applying the knowledge we learnt from class: Scale Invariant Feature Transform (SIFT) [7], match keypoints with RANSAC [4], and apply homography, mapping the Logo to the location in the given video clips [5].

The advantage of these sequence of operations over machine learning is that it only requires the minimum amount of data (1 is enough), and fast to apply, without the training process. While the drawback is also inevitable, which the SIFT [7] algorithm is very sensitive to noise. In addition, the algorithm is not prepared for multiple appearances of the same Logo. As shown in Fig 7, the Logo of NBC news is half-transparent, so the detection result is not optimal. While in a relatively stable, less noise environment Fig 8, the detection is more accurate.

By using this method, though we are unable to improve Recall, the it is able to improve Precision. This is done by pruning bad mapping points, such us negative width and height, or points that are mapped out of the image, we abandon the boundary box in these case.

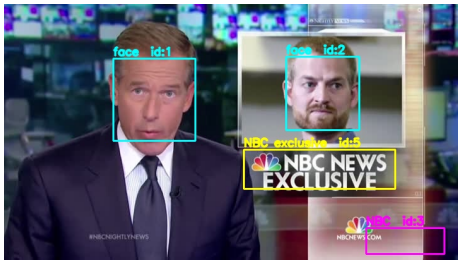

Figure 7: false Logo detection & positive face detection

Figure 8: positive Logo detection & face detection

3.2.1 Logo Detection Evaluation

[R:Recall, P:Precision, F1: F Score]
[C:Correct, M:Missed, F:False]

Logo	C	M	F	R	P	F1
nbc news	92	76	10	0.55	0.90	0.68
nbc excl	96	10	9	0.91	0.91	0.91
the voice	57	0	0	1.0	1.0	1.0
clevver	77	36	0	0.68	1.0	0.81
flick	22	8	0	0.73	1.0	0.85

Table 5: metrics of *Logo Detection* over all Logos

The outcome varies between Logo types. Like the one showed in Fig 8, the type of Logo with solid background (i.e Logo has high opacity) tend to be robust in detection. In this method, the transparency of the Logo introduces noice in position detection.

4 Face Tracking

Perform face tracking on video or real time camera helps gain both spatial and temporal information. The most difficult part lies on the assignment problem. Most algorithm perform assignment on consecutive frames. We have come up a simple method that performs tracking even between non-continues frames and shots.

4.1 Algorithm

Algorithm 1 Greedy Detection Tracking

```
initiate a MAX_HEAP
for object in 1st frame do
    MAX_SCORE = 1
    SECOND_MAX = 0
    for object in 2nd frame do
        calculate similarity score
        if score > MAX_SCORE then
            SECOND_MAX = MAX_SCORE
            MAX_SCORE = score
        end if
    end for
    if RATIO > THRESHOLD then
        prune the pair
    else
        push pair to heap
    end if
end for
while MAX_HEAP not empty do
    obj1, obj2 = MAX_HEAP.pop
    if obj2 already belongs to a tracking then
        continue
    end if
    if neither obj1 nor obj2 belongs to a tracking then
        initiate new tracking with obj1 and obj2
    end if
    if obj1 belongs to a track then
        add obj2 to the same track
    end if
end while
LEFT_OVER = [object in 1st frame not get paired]
carry LEFT_OVER to the next round
```

The algorithm starts from the very first two consecutive frames, the process it similar to find the matching in SIFT matching[7].

4.2 Similarity Function for tracking

The essential parts of performing an accurate object tracking are detection and similarity measurement. In this subsection, we talk about how we set up the similarity function. In order to determine if two objects are very similar, we focus on both color distribution and feature information. To tackle color problem, we chose the color histogram difference measurement, over all three channels, this give a detailed color difference of two images. For feature comparison, we chose Histograms of Oriented Gradients (HOG).

To compute HOG, we first calculate both the

magnitude and the direction of the gradients:

$$|\nabla I(x,y)| = \sqrt{I_x^2 + I_y^2}$$

$$\theta(x,y) = \arctan(I_y/I_x)$$

We take a 2×2 cell with each cell size of 8×8 pixel blocks sliding over the image, quantizing the directions into 9 bins with 20 degree increment. The gradient with larger magnitude votes into the bin. Then normalize 4 of such blocks together (2×2). So, in total, our similarity function S with Color Histogram difference CH_D and Histogram of Oriented Gradients difference HOG_D is:

$$S(I_1, I_2) = \frac{1}{HOG_D(I_1, I_2) + CH_D(I_1, I_2) + 1}$$

4.3 Performance

The algorithm works better in situation where number of people in the same scenes is small. Our algorithm can tackle discontinuous shot tracking (e.g identify and track people in 1st shot scene and 3rd scene). For frames that involves many people, it usually swaps the tacking suquence, like Fig 9 10

5 Gender Classification

Automated gender recognition is important in many applications such as biometric and human computer interaction. As a result, classifying gender from face images becomes an important research area. We tried two methods to perform this task.

5.1 ResNet18

Deeper neural networks turn out to be more powerful theoretically, but in practice they suffer from the degradation problem and are harder to train due to vanishing gradient. Residual blocks are proposed to solve this problem by using shortcut connections.

Figure 9: false Logo detection & positive face detection

Figure 10: positive Logo detection & face detection

We originally trained a residual network– Resnet18. This is an end-to-end approach, that we feed the model with an image and would directly obtain the class of it. Data are separated into training data and validation data in order to see the performance. Our neural net was trained with an Adam optimizer [6] and cross entropy loss. To fasten the training process, the model was trained with a minibatch of size 32. However, after 25 epochs, the training accuracy approached 100%, but validation accuracy is only around 80%, even after adding one dropout layer and applying weight decay. This implies that our model faces the problem of overfitting.

We thought this problem can be alleviated by employing more regularization techniques. However, training the neural net took a large amount of time. In my experiment, training 30 epochs requires more than 2 hours. Due to the time concerns, we didn't do lots of experiments

on it.

For further improvement, experiments such like cropping part of the image before feeding it to the neural net are considered. Also, representing the image in lower dimensional space may help since it decreases the number of parameters in the model.

5.2 Histogram of Oriented Gradient Feature

Another method we tried is simply extracting features from images and then feeding the features into a classifier. In real world, people may find that outline of faces contributes a lot to gender recognition from facial image. In order to represent the edge information, we choose the Histogram of Oriented Gradient[3] as the descriptor.

According to the paper [3], classic HOG features are obtained by normalizing the image, computing the gradient of each pixel, creating a histogram of edge directions and doing block normalization. One of the main contributions of the paper is that they use dense grid of cells, allowing overlapping both horizontally and vertically when sliding the windows. Also, for better accuracy, they apply local contrast normalization to each block before sending them to the classifier.

In my implementation, each individual histogram has 20 signed bins, with an interval length of 18.

Since people could tell the gender of a person from a black-white face image, I transformed the image to gray scale before extracting the HOG features. The only preprocessing we perform is image resizing. Observe that the resolution of image can affect the extracted edge feature. Images with low resolution contain mainly the information of position and coarse edges while large scale images include more of fine edges. Once a face is detected, it is cropped and resized to four scales—$16 \times 16, 32 \times 32, 64 \times 64, 128 \times 128$. Then the feature is extracted using a window of size $2 \times 2, 4 \times 4, 8 \times 8, 16 \times 16$ respectively, either with or without overlapping. After obtaining the input data, we fit a svm.SVC classifier to it and perform classification. [8].

5.2.1 Result

After comparing the accuracy scores on test data, I chose the classifier trained by 64×64 images with overlapped windows. Most faces in first two clips are classified correctly. Good results are in Fig 11, Fig 12. There are a few

Figure 11: Correct classifications from clip1.

failures shown in Fig13, Fig 14 The top example in 13 could be caused by the change of il-

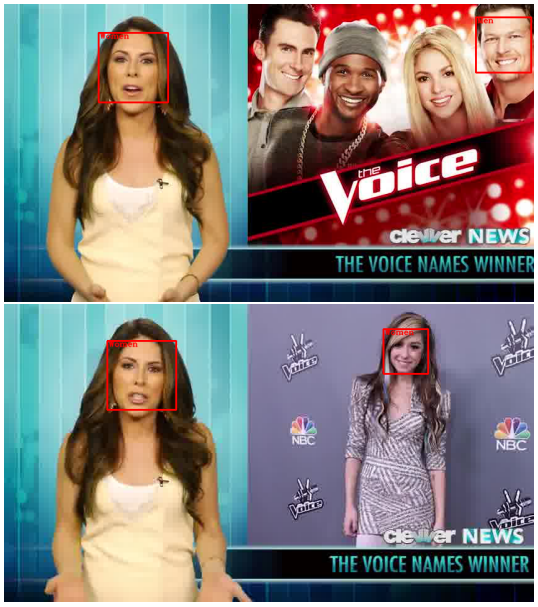

Figure 12: Correct classifications from clip2.

Figure 13: Bad results from clip1.

lumination within the face. This may give us a wrong edge which would influence the result. The potential reason for the other two failures could be the vague outlines.

But when applied the trained classifier to clip3, we obtained low precision with all classifiers. I found the outlines of faces in clip3 are not as clear as those in clip1 and clip2. This could be one possible reason for the failure, since the classifier is trained on edge features. Another possible reason is that faces in the training data set are mostly front faces, but in clip3, the man in the last frame bows his head. In order to improve the generalization of the classifier, we could include more images with various head poses in the training set.

5.2.2 Future Work

- As previously mentioned, the classifier may fail when faces are not perfectly front or edges are not clear. It could also fail when there exists a partial mask in the face. One improvement I could make is to gather

Figure 14: Bad result from clip2.

training images with different head poses and augment the input by smoothing the faces or applying masks on randomly chosen areas. Rotating or translating the training data may also help.

- The method has not yet been tested on other datasets. So, future work includes testing it on larger test sets.

- Alexandre and Lu (2010) [1] shows that decision fusion improves the result significantly. Instead of training a single classifier, this paper proposed to train various classifiers using different image scales or different features, predict the gender separately and make final decision via major-

ity vote. I think above approach can be included for the future improvement since given a specific image, some features may be easy to obtain while others are not. We're interested of extracting geometric face features such as the relative position of eyes, nose and lip, as well as texture features shown in the paper.

- Feature extraction process consumes a lot of time. This could be shorten by code optimization

6 Conclusion

In this project, we found that the traditional SVM classifier with facial feature performs well when the face edges are clear but with a large possibility to fail when the illumination varies. Also, the resolution of the face image would affect the classification results.

7 Contribution

Hirotaka Ishihara

- 3 shot detection
- face detection
- logo detection
- face tracking and similarity function
- all code above

Yichun Zhang

- gender classification

References

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Appendix

Decemnber 2019

1 Brief Pipline

Pipline Shot Detection

```
import numpy as np
import matplotlib.pyplot as plt
import cv2
import os
import sys
sys.path.insert(0, os.path.abspath('./'))

from utils import *
from ShotDetection import *

data = load_data()
shotDetector = ShotDetector(data)
```

```
clip_1 images importing...
clip_2 images importing...
clip_3 images importing...
Done !
```

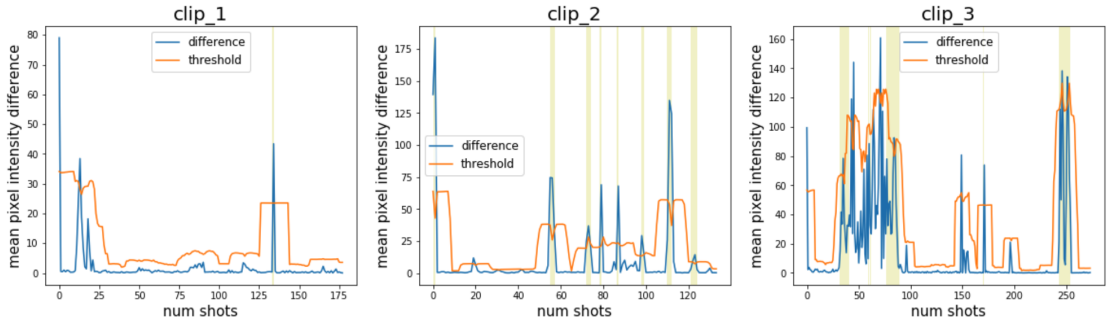
Shot Detection

Mean Pixel Intensity Measurement

```
shotDetector.show_detection('mean_pixel_intensity')
```

```
method used: mean_pixel_intensity

[Clip_1]   Recall: 1.00   Precision: 0.33   Combine: 0.50   Correct: 1   Missed: 0   False detect: 2
[Clip_2]   Recall: 1.00   Precision: 0.80   Combine: 0.89   Correct: 8   Missed: 0   False detect: 2
[Clip_3]   Recall: 0.67   Precision: 0.40   Combine: 0.50   Correct: 4   Missed: 2   False detect: 6
```

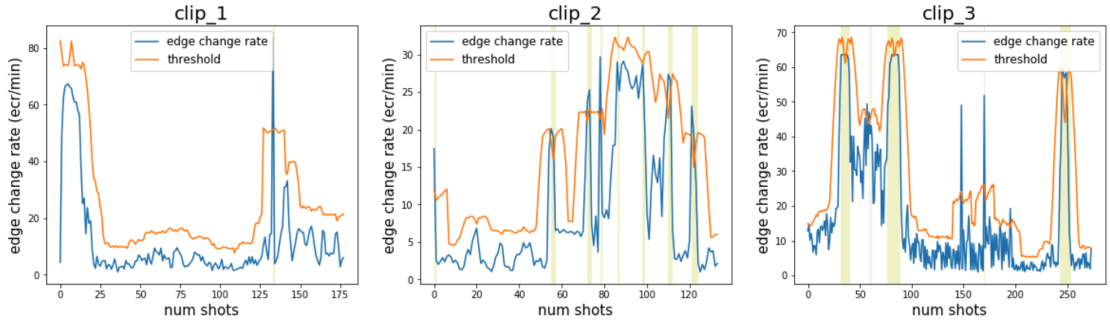


Edge Change Rate

```
shotDetector.show_detection('edge_change_rate', True)
```

```
method used: edge_change_rate

time used: 0.010544061660766602
[Clip_1]   Recall: 1.00   Precision: 1.00   Combine: 1.00   Correct: 1   Missed: 0   False detect: 0
time used: 0.0033278465270996094
[Clip_2]   Recall: 0.75   Precision: 1.00   Combine: 0.86   Correct: 6   Missed: 2   False detect: 0
time used: 0.002835988998413086
[Clip_3]   Recall: 0.83   click to scroll output; double click to hide   e: 0.71   Correct: 5   Missed: 1   False detect: 3
```

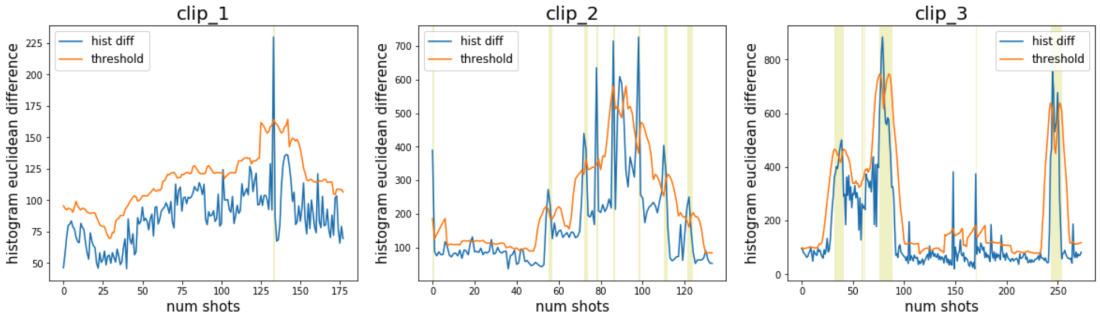


Color Histogram

```
: shotDetector.show_detection('color_histogram_difference', True)
```

```
method used: color_histogram_difference

time used: 0.013776063919067383
[Clip_1]   Recall: 1.00   Precision: 0.33   Combine: 0.50   Correct: 1   Missed: 0   False detect: 2
time used: 0.0026578903198242188
[Clip_2]   Recall: 1.00   Precision: 0.53   Combine: 0.70   Correct: 8   Missed: 0   False detect: 7
time used: 0.0028378963470458984
[Clip_3]   Recall: 0.67   Precision: 0.33   Combine: 0.44   Correct: 4   Missed: 2   False detect: 8
```



```
import os
import sys
import cv2
import matplotlib.pyplot as plt

from FaceDetector import *
from LogoDetector import *
from GenderDetector import *
from DetectorWraper import *
from utils import *
from config import *
from moviepy.editor import *


data = load_data()
```

```
clip_1 images importing...
clip_2 images importing...
clip_3 images importing...
Done !
```

1. load gender detector model ¶

```
gender = GenderDetector()
```

```
0.8571428571428571
```

2. Initiate all detectors need for a clip

```
detectorList = [FaceDetector(),
#                 LogoDetector('NBC'),
#                 LogoDetector('NBC exclusive'),
#                 LogoDetector('voice'),
#                 LogoDetector('clevver news'),
                LogoDetector('super woman'),
                LogoDetector('flick'),
#                 LogoDetector('marvel'),
               ]

detector = DetectorWraper(detectorList, CLIP_3, gender)
# image = detector.visualize_detection(image)
```

```
detector.tracking(data["X"][2], 0.5, relabel=True)
```

1.1 Python Files

DetectorWaper.py

```
1
2  import cv2
3  import numpy as np
4  import heapq
5  from skimage.feature import hog
6  from config import *
7  from utils import *
8
9
10 class DetectorWraper(object):
11   """
12   A class that contains all the detectors need for a clip detection
13   """
14   def __init__(self, detectors, clip, genderDetect=None):
15     self.clip = clip
16     self.genderDetect = genderDetect
17     self.detectors = []
18     for detector in detectors:
```

```
      self.detectors.append(detector)
    self.num_save = 0
    # later greedy algorithm for tracking
    self.num_detect = 0
    self.detection_frames = {}
    self.detection_index= {}
    self.track_frame = None

  def apply_detection(self, image):
    """
    Return a list of tuple: List[(text, position)]
    """
    pos_list = []
    for c in self.detectors:
      pos_list += c.get_position(image)
    return pos_list

  def visualize_detection(self, image):
    """
    Return a image with visualized locations detected
    """
    H, W, _ = image.shape
    pos_list = self.apply_detection(image)
    detections = {}
    hasDetection = False
    for i, L in enumerate(pos_list):
      text, coordinates = L[0], L[1]
      COLOR = COLORS[text]
      for x, y, w, h in coordinates:
        # prune bad homography points
        if x < 0 or y < 0 or x + w > W or \
           y + h > H or w <= 1 or h <= 1:
          continue
        # add the detection to the dict for tracking
        detections[self.num_detect] = (x, y, w, h)
        self.detection_index[self.num_detect] = (x, y, w, h, self.num_save, text)
        self.num_detect += 1
        hasDetection = True
        # if the detection is human
        if text == 'face':
          gender = self.genderDetect.classify(image[y:y+h, x:x+w, :])
          gender = 'female' if gender[0] < 0.5 else 'male'
          cv2.putText(image, gender, (x + w // 2, y + h + 5),
            cv2.FONT_HERSHEY_SIMPLEX, 0.6, COLOR, 2, cv2.LINE_AA)

        image = cv2.rectangle(image, (x, y), (x + w, y + h), COLOR, 2)
        cv2.putText(image, text, (x, y - 5),
          cv2.FONT_HERSHEY_SIMPLEX, 0.6, COLOR, 2, cv2.LINE_AA)
    if hasDetection:
      self.detection_frames[self.num_save] = detections
    self.num_save +=1
    return image
```

```
71
72  def save_detection(self, image):
73    """
74    Save the visualized image
75    """
76    img = self.visualize_detection(image)
77    img = cv2.cvtColor(img, cv2.COLOR_RGB2BGR)
78    cv2.imwrite(f'{SAVE_PATH}{self.clip}{self.num_save}.jpg', img)
79
80  def tracking(self, frameList, thres, relabel=False):
81    '''
82    Perform detection tracking.
83    Input: the list the video frames frameList
84    Output: Example:  1. Dict{'track 1':[obj_1, obj_3], 'track 2': [obj_2] ...}
85    '''
86    if relabel:
87      print('detecting objects ...')
88      for frame in frameList:
89        self._get_positions(frame)
90    track_obj = {}
91    track_frame = {}
92    num_track = 0
93    left_over = []
94    detected_frames = list(self.detection_frames.keys())
95
96    print('start tracking ...')
97    for i, frame in enumerate(detected_frames[:-1]):
98      # extact frame image
99      img1 = frameList[detected_frames[i]]
100     img2 = frameList[detected_frames[i + 1]]
101     # frame detections
102     frame_1 = self.detection_frames[detected_frames[i]]
103     frame_2 = self.detection_frames[detected_frames[i + 1]]
104     # detection id
105     detects_1 = list(frame_1.keys())
106     detects_2 = list(frame_2.keys())
107
108     # =============  frame wise compare stage (consectutive) =============
109     # init a heap for later ranking
110     HEAP = []
111     # get only human left over
112     only_human = []
113     detects_1 += left_over
114     for obj_1 in detects_1:
115       max_score = -9999
116       next_score = -9999
117       pair = None
118       ratio = None
119       x1, y1, w1, h1, f, text1, _ = self.detection_index[obj_1]
120       # pnly track human
121       if text1 != 'face' and text1 != 'super woman':
122         continue
```

```
        only_human.append(obj_1)
        for obj_2 in detects_2:
          x2, y2, w2, h2, _, text2, _ = self.detection_index[obj_2]
          # only track human
          if text2 != 'face' and text2 != 'super woman':
            continue

          patch_1 = img1[y1 : y1 + h1, x1 : x1 + w1, :]
          patch_2 = img2[y2 : y2 + h2, x2 : x2 + w2, :]
          score = self.similarity_score(patch_1, patch_2)

          if score > max_score:
            next_score = max_score
            max_score = score
            pair = obj_1, f, obj_2
            ratio = next_score / max_score
        # calculate min over max ratio
        if ratio is None or ratio > thres:
          continue
        else: heapq.heappush(HEAP, (-max_score, (pair[0], pair[1], pair[2])))

      # =================  track adding stage  =================
      repeated_obj1 = []
      repeated_obj2 = []
      for _ in range(len(HEAP)):
        track = heapq.heappop(HEAP)
        obj_1, frame_idx, obj_2 = track[1]
        # if already paired, skip
        if obj_2 in repeated_obj2:
          continue

        repeated_obj1.append(obj_1)
        repeated_obj2.append(obj_2)

        isPreviousTracked = False
        for track_id in track_obj.keys():
          if obj_1 in track_obj[track_id]:
            track_obj[track_id].append(obj_2)
            x, y, w, h, f, t, _ = self.detection_index[obj_2]
            self.detection_index[obj_2] = (x, y, w, h, f, t, track_id)
            isPreviousTracked = True
            break
        if isPreviousTracked:
          continue
        # if no previous track, add new one
        track_obj[num_track] = [obj_1, obj_2]
        x1, y1, w1, h1, f1, t1, _ = self.detection_index[obj_1]
        x2, y2, w2, h2, f2, t2, _ = self.detection_index[obj_2]
        self.detection_index[obj_1] = (x1, y1, w1, h1, f1, t1, num_track)
        self.detection_index[obj_2] = (x2, y2, w2, h2, f2, t2, num_track)
        num_track += 1

```

```
      left_over = [obj for obj in only_human if obj not in repeated_obj1]
      print(len(left_over))

    self.track_obj = track_obj
    print('saving annotations ...')
    self._annotate_images(frameList)
    print('Done !')

  def _get_positions(self, image):
    """
    SHOULD NOT BE CALL EXPLICITY, HIDDEN FUNCTION
    return detection postion without visualize positon
    """
    H, W, _ = image.shape
    pos_list = self.apply_detection(image)
    detections = {}
    hasDetection = False
    for i, L in enumerate(pos_list):
      text, coordinates = L[0], L[1]
      for x, y, w, h in coordinates:
        if x < 0 or y < 0 or x + w > W or \
           y + h > H or w <= 1 or h <= 1:
          continue
        # add the detection to the dict for tracking
        if text == 'face' or text == 'super woman':
          self.detection_index[self.num_detect] = (x, y, w, h, self.num_save, text, -1)
        else:
          self.detection_index[self.num_detect] = (x, y, w, h, self.num_save, text, -2)
        detections[self.num_detect] = (x, y, w, h)
        self.num_detect += 1
        hasDetection = True
    if hasDetection:
      self.detection_frames[self.num_save] = detections
    self.num_save +=1

  def _annotate_images(self, frameList):
    """
    SHOULD NOT BE CALL EXPLICITY, HIDDEN FUNCTION
    annotate positions in each frames with given frames
    """
    image_array = frameList
    for i, image in enumerate(image_array):
      if i in list(self.detection_frames.keys()):
        for obj in list(self.detection_frames[i].keys()):
          x, y, w, h, frame, text, track_id = self.detection_index[obj]
          COLOR = COLORS[text]
          # if the detection is human
          if text == 'face':
            text = text + "  id:{}".format(track_id)
            # predict
            gender = self.genderDetect.classify(image[y:y+h, x:x+w, :])
            gender = 'female' if gender[0] < 0.5 else 'male'
```

```
            cv2.putText(image, gender, (x + w // 2 - 10, y + h + 15),
              cv2.FONT_HERSHEY_SIMPLEX, 0.6, COLOR, 2, cv2.LINE_AA)

          image_array[i] = cv2.rectangle(image_array[i], (x, y), (x + w, y + h), COLOR,
    2)
          cv2.putText(image_array[i], text, (x, y - 5),
            cv2.FONT_HERSHEY_SIMPLEX, 0.6, COLOR, 2, cv2.LINE_AA)


      cv2.imwrite(f'{SAVE_PATH}{self.clip}{i}.jpg', image_array[i])

  def similarity_score(self, img1, img2):
    """
    Calculate the similarity score used for detection tracking
    """
    # resize into the same shape first
    if img1.shape != img2.shape:
      v, h = max(img1.shape[0], img2.shape[0]), max(img1.shape[1], img2.shape[1])
      dim = (h, v)
      h_scale = min(img1.shape[1], img2.shape[1]) / h
      v_scale = min(img1.shape[0], img2.shape[0]) / v
      img1 = cv2.resize(img1, dim, interpolation = cv2.INTER_AREA)
      img2 = cv2.resize(img2, dim, interpolation = cv2.INTER_AREA)
    # histogram
    diff = 0
    for c in range(3):
      hist1 = cv2.calcHist([img1], [c], None, [256], [0, 256])
      hist2 = cv2.calcHist([img2], [c], None, [256], [0, 256])
      diff += np.linalg.norm(hist1 - hist2)

    # HoG
    fd1, _ = hog(img1, orientations=8, pixels_per_cell=(16, 16),
                    cells_per_block=(1, 1), visualize=True, multichannel=True)
    fd2, _ = hog(img2, orientations=8, pixels_per_cell=(16, 16),
                    cells_per_block=(1, 1), visualize=True, multichannel=True)
    # Combine both
    dist = np.linalg.norm(fd1 - fd2)
    aim = mean_pixel_intensity_diff(img1, img2)
    score = 1 / (dist + diff + aim + 1)
    return score
```

GenderDetector.py

```
import glob
from skimage import transform
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
import cv2

from config import *

class GenderDetector(object):
    """
    A class detect gender given detected faces
    """
    def __init__(self, img_size=64, window_size=(8, 8), overlap=2, intrvlInDegree=18):
        self.img_size = img_size
        self.window_size = window_size
        self.overlap = overlap
        self.intrvlInDegree = intrvlInDegree
        self.data_0 = self._get_train_data(female_path)
        self.data_1 = self._get_train_data(male_path)
        self.classifier = self._get_shape_classifier()


    def classify(self, face):
        """
        classify female or male given croped face
        """
        face = self._resize_image(face)
        feature = self._get_shape_feature(face)
        feature = np.array(feature)
        feature = feature.reshape((1, feature.shape[0]*feature.shape[1]))
        result = self.classifier.predict(feature)
        return result


    def _detect_face(self, img, min_nghb=5):
        """
        Detect face, used to training
        """
        face_cascade = cv2.CascadeClassifier(train_svm)
        img_gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
        faces = face_cascade.detectMultiScale(img_gray, minNeighbors=min_nghb, minSize
    =(30,30))
        crops = [] #store in a list, can think of converting to an array if vectorization
     helps
        for (x,y,w,h) in faces:
            crops.append(img_gray[y:y+h, x:x+w])
        return crops

    def _resize_image(self, img):
        return transform.resize(img, (self.img_size, self.img_size), mode='reflect',
```

```
    anti_aliasing=True)

    def _get_train_data(self, path):
        img_paths = glob.glob(pathname=path)
        imgs =  [cv2.cvtColor(cv2.imread(img_path),cv2.COLOR_BGR2RGB) for img_path in
    img_paths]
        data = []
        for image in imgs:
            crops = self._detect_face(image)
            data.extend([self._resize_image(crop) for crop in crops])
        return data

    def _get_shape_feature(self, img):
        if not 360%self.intrvlInDegree == 0:
            raise RuntimeError
        elif img.shape[0]%self.window_size[0]!=0 or img.shape[1]%self.window_size[1]!=0:
            raise RuntimeError
        else:
        #     Compute image gradient using Sobel filter
            sobelx =  cv2.Sobel(img,cv2.CV_64F,1,0,ksize=3)
            sobely =  cv2.Sobel(img,cv2.CV_64F,0,1,ksize=3)

        #     Get the gradient magnitude and orientation
            magnitudes = np.round(np.hypot(sobelx, sobely))
            angles = cv2.phase(sobelx, sobely, angleInDegrees=True)

        #     Divide angle by the length of interval(e.g. 18), take the floor of that
    number, then we get class for each gradient
            categories = np.floor_divide(angles, self.intrvlInDegree)
    #         print("Category\n", categories.shape, categories)
        #     Compute total number of windows
            num_window = (self.overlap*img.shape[0]//self.window_size[0])*(self.overlap*
    img.shape[1]//self.window_size[1])

        #     Create the storage space for the image feature
            feature = np.zeros((num_window, 360//self.intrvlInDegree))

            window_idx = 0
            for i in range(0, img.shape[0], self.window_size[0]//self.overlap):
                for j in range(0, img.shape[1], self.window_size[1]//self.overlap):
    #                 print("window", window_idx, "\n")
                    magn_window = magnitudes[i:i+self.window_size[0], j:j+self.
    window_size[1]].flatten()
                    category_window = categories[i:i+self.window_size[0], j:j+self.
    window_size[1]].flatten()

                    for idx_bin in range(360//self.intrvlInDegree):
        #                 Sum the maginitude where the angle is in the current interval
    range(category)
                        indices = np.argwhere(category_window==idx_bin)
                        feature[window_idx, idx_bin] = np.sum(magn_window[indices])
    #                 print("Current feature window: \n", feature[window_idx, :])
```

```
    #                 Increment the index of window
                    window_idx += 1
        return feature

    def _get_shape_classifier(self):
        features_0 = []
        features_1 = []
    #     Extract shape features for both classes
        for img in self.data_0:
            feature = self._get_shape_feature(img)
            features_0.append(feature.flatten())
        for img in self.data_1:
            feature = self._get_shape_feature(img)
            features_1.append(feature.flatten())
    #     Turn it from list to numpy array
        features_0 = np.stack(features_0)
        features_1 = np.stack(features_1)

    #     Label the features
        features_l0 = np.column_stack((features_0, np.zeros(features_0.shape[0])))
        features_l1 = np.column_stack((features_1, np.ones(features_1.shape[0])))
    #     Combine two classes together
        features_labeled = np.vstack((features_l0, features_l1))
    #     Shuffle the data
        features_labeled = np.random.permutation(features_labeled)

    #     Split it to X and y
        X = features_labeled[:, :features_labeled.shape[1]-1]
        y = features_labeled[:, -1]

        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

        svcclassifier = SVC(kernel='linear')
        svcclassifier.fit(X_train, y_train)
    #     Compute the accuracy using cross validation
        print(svcclassifier.score(X_test,y_test))
        return svcclassifier
```

LogoDetector.py

```
import cv2
import itertools
from config import *
from utils import *

COLOR = COLORS['face']
sift = cv2.xfeatures2d.SIFT_create()


class LogoDetector(object):
  """
  A class performs Logo detection given video clips
  """
  def __init__(self, logName):
```

```
    self.match = cv2.BFMatcher(cv2.NORM_L1, crossCheck=False)
    template = cv2.imread(LOGO[logName])
    self.template = cv2.cvtColor(template, cv2.COLOR_RGB2GRAY)
    self.logName = logName

  def get_position(self, image):
    """
    Return position list
    """
    image = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
    # do rancan and homography
    pos = self._homography(image)
    if pos is None:
      return []
    top_l, bottom_l, bottom_r, top_r = pos
    x, y = top_l[0], top_l[1]
    w, h = top_r[0] - top_l[0], bottom_l[1] - top_l[1]
    return [[self.logName, [(x, y, w, h)]]]

  def _visualize_detection(self, pos_list, image):
    """
    Visualize detection
    """
    for i, L in enumerate(pos_list):
      text, coordinates = L[0], L[1]
      for x, y, w, h in coordinates:
        image = cv2.rectangle(image, (x, y), (x + w, y + h), COLOR, 2)
        cv2.putText(image, text, (x, y - 5),
          cv2.FONT_HERSHEY_SIMPLEX, 0.6, COLOR, 1, cv2.LINE_AA)
    return image

  def _homography(self, image):
    """
    Compute homography from image to the given video clip
    """
    # get matching points
    kp1, des1 = sift.detectAndCompute(image, None)
    kp2, des2 = sift.detectAndCompute(self.template, None)
    bf = cv2.BFMatcher()
    matches = bf.knnMatch(des1, des2, k=2)
    good = []
    # prune the matching
    for m,n in matches:
      if m.distance < 0.5 * n.distance:
          good.append([m])
    # if no good matching, return
    if len(good) < 4:
      return
    # extract location info from matching point
    kp1_index = [m[0].queryIdx for m in good]
    kp2_index = [m[0].trainIdx for m in good]
    kp1 = np.array([k.pt for k in np.array(kp1)[kp1_index]])
```

```
    kp2 = np.array([k.pt for k in np.array(kp2)[kp2_index]])
    # calculate homography using RANSAC
    H, _ =  cv2.findHomography(kp2, kp1, cv2.RANSAC, 0.1)
    if H is None:
      return
    # get location of the self.template in the image
    height, width = self.template.shape
    top_left = H.dot(np.array([[0, 0, 1]]).reshape(3, 1)).flatten()
    bottom_left = H.dot(np.array([[0, height, 1]]).reshape(3, 1)).flatten()
    bottom_right = H.dot(np.array([[width, height, 1]]).reshape(3, 1)).flatten()
    top_right = H.dot(np.array([[width, 0, 1]]).reshape(3, 1)).flatten()
    # rescale the points
    top_left = top_left[:2] / top_left[-1]
    bottom_left = bottom_left[:2] / bottom_left[-1]
    bottom_right = bottom_right[:2] / bottom_right[-1]
    top_right = top_right[:2] / top_right[-1]
    # int type
    top_left = top_left.astype(int)
    bottom_left = bottom_left.astype(int)
    bottom_right = bottom_right.astype(int)
    top_right = top_right.astype(int)

    return top_left, bottom_left, bottom_right, top_right
```

FaceDetector.py

```
import cv2
import numpy as np
from config import *
from utils import *

COLOR = COLORS['face']


class FaceDetector(object):
  """
  A class performs face detect in video clips
  """
  def __init__(self, List=[face1, face2, profile1, profile2]):
    self._classifiers = []
    for xml in List:
      self._classifiers.append(cv2.CascadeClassifier(xml))
    self.category = 'face'

  def get_position(self, image):
    """
    Return list of positions that detected faces
    """
    image = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
    pos = []
    for c in self._classifiers:
      p = c.detectMultiScale(image, 1.3, 3)
      if len(p) != 0:
        pos += p.tolist()
```

```
    pos_list = self._prune_overlap(pos)
    return [['face', pos_list]]

  def _visualize_detection(self, pos_list, image):
    """
    Visualize the face detection
    """
    for i, L in enumerate(pos_list):
      text, coordinates = L[0], L[1]
      for x, y, w, h in coordinates:
        image = cv2.rectangle(image, (x, y), (x + w, y + h), COLOR, 2)
        cv2.putText(image, text, (x, y - 5),
          cv2.FONT_HERSHEY_SIMPLEX, 0.7, COLOR, 2, cv2.LINE_AA)
    return image

  def _prune_overlap(self, List):
    """
    prune face detection with overly larged overlap
    """
    result = []
    for pos in List:
      if len(result) == 0:
        result.append(pos)
        continue
      include = True
      for old_pos in result:
        overlap = self._overlap(pos, old_pos)
        if overlap > 0.2:
          include = False
      if include:
        result.append(pos)
    return result

  def _overlap(self, pos1, pos2):
    """
    Calculate IoU region given two boxes
    """
    x1, y1, w1, h1 = pos1
    x2, y2, w2, h2 = pos2
    # calculate the intersection
    top = max(x1, x2), min(y1 + h1, y2 + h2)
    bottom = min(x1 + w1, x2 + w2), max(y1 + h1, y2 + h2)
    interset = max(0, min(y1 + w1, y2 + w2) - max(y1, y2)) * \
           max(0, min(x1 + w1, x2 + w2) - max(x1, x2))
    # calculate the union + intersection
    union1 = w1 * h1
    union2 = w2 * h2

    return interset / float(union1 + union2 - interset)
```

ShotDetector.py

```
import matplotlib.pyplot as plt
import numpy as np
```

```
import time
from tempfile import TemporaryFile
from utils import *
from config import *

MEAN_PIXEL_INTENSITY = 'mean_pixel_intensity'
ECR = 'edge_change_rate'
HIST_DIFF = 'color_histogram_difference'


class ShotDetector(object):
    """
    A class detect shot transitions given video clips
    """
    def __init__(self, data):
        self.data = data
        self.img_array1 = data['X'][0]
        self.img_array2 = data['X'][1]
        self.img_array3 = data['X'][2]

    def show_detection(self, method, *arg):
        """
        Creat plot of shot detection and the threshold given 'method'
        """
        if method == MEAN_PIXEL_INTENSITY:
            print(f'method used: {MEAN_PIXEL_INTENSITY}\n')
            if len(arg) > 0:
                self._mean_p_int(window_size=arg[0], T=arg[1])
            else: self._mean_p_int()
        elif method == ECR:
            print(f'method used: {ECR}\n')
            if len(arg) > 0:
                self._edge_change_rate(load=arg[0])
            else: self._edge_change_rate()
        elif method == 'color_histogram_difference':
            print(f'method used: {HIST_DIFF}\n')
            if len(arg) > 0:
                self._hist_diff(load=arg[0])
            else: self._hist_diff()
        else:
          raise Exception(f"Method <{method}> valid")

    # ============================== hidden function ==========================

    def _mean_p_int(self, window_size=15, T=4):
        """
        Apply mean intensity measurement
        """
        window_sizes, Ts = [19, 15, 15], [5, 2, 7]
        fig = plt.figure(figsize=(20, 5))
        for clip in range(3):
            window_size, T, diff = window_sizes[clip], Ts[clip], []
```

```
            img_array = self.data['X'][clip]
            # clip 1
            for i in range(len(img_array) - 1):
                diff.append(mean_pixel_intensity_diff(img_array[i - 1], img_array[i]))
            frames, thres = adaptive_threshold(diff, window_size=window_size, T=T)
            # plot clip
            plt.subplot(1, 3, clip + 1)
            plt.plot(np.arange(len(diff)), diff, label='difference')
            plt.plot(np.arange(len(thres)), thres, label='threshold')
            for shots in self.data['Y'][clip].tolist():
              plt.axvspan(shots[0], shots[1], facecolor='y', alpha=0.2)
            plt.xlabel('num shots', size=15)
            plt.ylabel('mean pixel intensity difference', size=15)
            plt.legend(fontsize=12)
            plt.title(f'clip_{clip + 1}', size=20)
            # brief evaluate
            Recall, Precision, Combine, C, M, F = Evaluate(frames, self.data['Y'][clip])
            print(f"[Clip_{clip + 1}]   Recall: {Recall:.2f}" + \
                f"   Precision: {Precision:.2f}   Combine: {Combine:.2f}    Correct: {C}"
    + \
                f"   Missed: {M}    False detect: {F}")
        plt.show()

    def _edge_change_rate(self, load=True):
        """
        Apply Edge Change Ratio
        """
        window_sizes, Ts = [15, 13, 19], [6, 3, 3]
        fig = plt.figure(figsize=(20, 5))
        for clip in range(3):
            window_size, T, ecr = window_sizes[clip], Ts[clip], []
            img_array = self.data['X'][clip]
            # clip 1
            start = time.time()
            if load:
                try:
                  ecr = np.load(f'{CACHE}ecr_ecr_{clip}.npy')
                  frames = np.load(f'{CACHE}frames_ecr_{clip}.npy')
                  thres = np.load(f'{CACHE}thres_ecr_{clip}.npy')
                except:
                  for i in range(1, len(img_array)):
                      ecr.append(EdgeChangeRate(img_array[i - 1], img_array[i], sigma=3))
                  # apply threshold
                  ecr = ecr / np.min(ecr)
                  frames, thres = adaptive_threshold(ecr, window_size=window_size, T=T)
                  np.save(f'{CACHE}ecr_ecr_{clip}.npy', ecr)
                  np.save(f'{CACHE}frames_ecr_{clip}.npy', frames)
                  np.save(f'{CACHE}thres_ecr_{clip}.npy', thres)
            else:
                for i in range(1, len(img_array)):
                    ecr.append(EdgeChangeRate(img_array[i - 1], img_array[i], sigma=3))
                # apply threshold
```

```
                ecr = ecr / np.min(ecr)
                frames, thres = adaptive_threshold(ecr, window_size=window_size, T=T)
                np.save(f'{CACHE}ecr_ecr_{clip}.npy', ecr)
                np.save(f'{CACHE}frames_ecr_{clip}.npy', frames)
                np.save(f'{CACHE}thres_ecr_{clip}.npy', thres)


            print(f"time used: {time.time() - start}")
            # plot clip
            plt.subplot(1, 3, clip + 1)
            plt.plot(np.arange(len(ecr)), ecr, label='edge change rate')
            plt.plot(np.arange(len(thres)), thres, label='threshold')
            for shots in self.data['Y'][clip].tolist():
              plt.axvspan(shots[0], shots[1], facecolor='y', alpha=0.2)
            plt.xlabel('num shots', size=15)
            plt.ylabel('edge change rate (ecr/min)', size=15)
            plt.legend(fontsize=12)
            plt.title(f'clip_{clip + 1}', size=20)
            # brief evaluate
            Recall, Precision, Combine, C, M, F = Evaluate(frames, self.data['Y'][clip])
            print(f"[Clip_{clip + 1}]   Recall: {Recall:.2f}" + \
          f"   Precision: {Precision:.2f}   Combine: {Combine:.2f}    Correct: {C}" + \
          f"   Missed: {M}    False detect: {F}")
        plt.show()

    def _hist_diff(self, load=True):
        """
        Apply histogram difference
        """
        window_sizes, Ts = [19, 13, 19], [7, 5, 6]
        fig = plt.figure(figsize=(20, 5))
        for clip in range(3):
            window_size, T, hist_diff = window_sizes[clip], Ts[clip], []
            img_array = self.data['X'][clip]
            # clip 1
            start = time.time()
            if load:
                try:
                  hist_diff = np.load(f'{CACHE}diff_hist_{clip}.npy')
                  frames = np.load(f'{CACHE}frames_hist_{clip}.npy')
                  thres = np.load(f'{CACHE}thres_hist_{clip}.npy')
                except:
                    for i in range(1, len(img_array)):
                        hist_diff.append(color_hist_diff(img_array[i - 1], img_array[i],
32))
                  # apply threshold
                    frames, thres = adaptive_threshold(hist_diff, window_size=window_size
, T=T)
                    np.save(f'{CACHE}diff_hist_{clip}.npy', hist_diff)
                    np.save(f'{CACHE}frames_hist_{clip}.npy', frames)
                    np.save(f'{CACHE}thres_hist_{clip}.npy', thres)
            else:
```

```
                for i in range(1, len(img_array)):
                    hist_diff.append(color_hist_diff(img_array[i - 1], img_array[i], 32))
                # apply threshold
                frames, thres = adaptive_threshold(hist_diff, window_size=window_size, T=
    T)
                np.save(f'{CACHE}diff_hist_{clip}.npy', hist_diff)
                np.save(f'{CACHE}frames_hist_{clip}.npy', frames)
                np.save(f'{CACHE}thres_hist_{clip}.npy', thres)

            print(f"time used: {time.time() - start}")
            # plot clip
            plt.subplot(1, 3, clip + 1)
            plt.plot(np.arange(len(hist_diff)), hist_diff, label='hist diff')
            plt.plot(np.arange(len(thres)), thres, label='threshold')
            for shots in self.data['Y'][clip].tolist():
                plt.axvspan(shots[0], shots[1], facecolor='y', alpha=0.2)
            plt.xlabel('num shots', size=15)
            plt.ylabel('histogram euclidean difference', size=15)
            plt.legend(fontsize=12)
            plt.title(f'clip_{clip + 1}', size=20)
            # brief evaluate
            Recall, Precision, Combine, C, M, F = Evaluate(frames, self.data['Y'][clip])
            print(f"[Clip_{clip + 1}]   Recall: {Recall:.2f}" + \
          f"   Precision: {Precision:.2f}   Combine: {Combine:.2f}    Correct: {C}" + \
          f"   Missed: {M}    False detect: {F}")
        plt.show()
```

utils.py

```
import numpy as np
import numba
from numba import jit
import cv2
import glob
from moviepy.editor import *
import matplotlib.pyplot as plt
from scipy import ndimage
from skimage import color, feature, transform

data = './data/'

@numba.jit(forceobj=True)
def load_data():
    """
    load all three clips to a dict variable
    """
    # ================== first clip ==================
    print('clip_1 images importing...')
    fileName1 = sorted(glob.glob(data + 'clip_1/*.jpg'))
    img1 = [cv2.imread(img) for img in fileName1]
    label1 = np.zeros((len(img1), 1))
    shot1 = np.array([(133, 134)])
    # ================== second clip ==================
    print('clip_2 images importing...')
```

```
    fileName2 = sorted(glob.glob(data + 'clip_2/*.jpg'))
    img2 = [cv2.imread(img) for img in fileName2]
    label2 = np.zeros((len(img2), 1))
    shot2 = np.array([(0, 1), (55, 57), (72, 74), (78, 79),
                      (86, 87), (98, 99), (110, 112), (121, 124)])
    # ================== third clip ==================
    print('clip_3 images importing...')
    fileName3 = sorted(glob.glob(data + 'clip_3/*.jpg'))
    img3 = [cv2.imread(img) for img in fileName3]
    label3 = np.zeros((len(img3), 1))
    shot3 = np.array([(32, 41), (59, 60), (61, 62),
                      (76, 89), (170, 171), (243, 254)])
    print('Done !')
    test = {'X': [img1, img2, img3], 'Y': [shot1, shot2, shot3]}
    return test

def image_to_video(path):
    images = sorted(glob.glob(path + '*.jpg'))
    clips = [ImageClip(m).set_duration(2) for m in images]
    concat_clip = concatenate_videoclips(clips, method="compose")
    concat_clip.write_videofile(path + "test.mp4", fps=3)

def color_hist_diff(image1, image2, patch_size=16):
    """
    calculate the color histogram difference of two images
    """
    # get dimesion and patch
    vertical, horizontal, Z = image1.shape
    v_patch = vertical // 16
    h_patch = horizontal // 16
    # calculate difference
    diff = 0
    for z in range(Z):
        img1, img2 = image1[:, :, z], image2[:, :, z]
        for i in range(0, img1.shape[0] - v_patch + 1, patch_size):
            for j in range(0, img1.shape[1] - h_patch + 1, patch_size):
                patch1 = img1[i:i + v_patch, j:j + h_patch].flatten()
                patch2 = img2[i:i + v_patch, j:j + h_patch].flatten()
                hist1 = np.histogram(patch1, bins=np.arange(257), density=True)
                hist2 = np.histogram(patch2, bins=np.arange(257), density=True)
                diff += np.linalg.norm(hist1[0] - hist2[0])
    return diff

def mean_pixel_intensity_diff(img1, img2):
  diff = 0
  for z in range(img1.shape[-1]):
    diff += np.abs(np.mean(img1[:,:,z]) - np.mean(img2[:,:,z]))
  return diff

# ========================== calculate Edge Change Ratio ==========================

@numba.jit(forceobj=True)
```

```
def EdgeChangeRate(img1, img2, iteration=1, sigma=5):
    # convert to gray
    gray1 = color.rgb2gray(img1)
    gray2 = color.rgb2gray(img2)
    # get white background and edge
    black1 = feature.canny(gray1, sigma=sigma).astype("uint8")  # background: 0  edge: 1
    black2 = feature.canny(gray2, sigma=sigma).astype("uint8")
    # count number of edge pixel
    E1 = max(np.sum(black1 == 1), 0.1)
    E2 = max(np.sum(black2 == 1), 0.1)
    # dilate both image
    kernel = np.ones((3, 3)).astype("uint8")
    dilate1 = cv2.dilate(black1, kernel).astype("uint8")
    dilate2 = cv2.dilate(black2, kernel).astype("uint8")
    # combine
    imgIn = black1 * dilate2
    imgOut = black2 * dilate1
    # count edge change pixel
    C1 = np.sum(imgIn == 1)
    C2 = np.sum(imgOut == 1)

    return max(1 - min(C1 / E2, C2 / E1), 0)


# ================================== get result ==================================

def adaptive_threshold(dissimilarity, window_size=9, T=5):
  # Dugad el. al Model
  if type(dissimilarity) != np.ndarray:
    dissimilarity = np.array(dissimilarity)
  # split into two windows
  w = window_size // 2
  dissimilarity = np.pad(dissimilarity, pad_width=w, mode='constant')
  thresholds = []
  for i in range(w, len(dissimilarity) - w):
    left  = dissimilarity[i - w : i]
    right = dissimilarity[i : i + w]
    threshold = max(np.mean(left)  + T * np.sqrt(np.std(left)),
              np.mean(right) + T * np.sqrt(np.std(right)))
    thresholds.append(threshold)

  shot_index = np.arange(len(dissimilarity) - window_size + 1)[dissimilarity[w : - w] >
    thresholds]
  return shot_index, thresholds


# ================================== Evaluation ==================================

def Evaluate(pred, target):
    # C: correct detection
    # M: missed detection
    # F: false detection
```

```
    C, M, F = 0, 0, 0
    # pred may have multiple frames detection for dissolve
    total_correct = 0
    for shot in target:
        # count for dissolve
        if type(shot) not in [int, float]:
            # output correcly predict one of the dissolve frames
            detected = sum([output in range(shot[0], shot[1] + 1) for output in pred])
            C += 1 if detected > 0 else 0
            M += 0 if detected != 0 else 1
            total_correct += detected
        # hard cut case
        else:
            C += 1 if shot in pred else 0
            M += 0 if shot in pred else 1
            total_correct += 1 if shot in pred else 0
    # false detection
    F = len(pred) - total_correct
    # Recall
    Recall = C / (C + M)
    Precision = C / (C + F) if (C + F) != 0 else 0
    Combine = 2 * Recall * Precision / (Recall + Precision) if (Recall + Precision) != 0
    else 0
    return Recall, Precision, Combine, C, M, F
```

config.py

```
"""
Configurations for the entire project
"""

# color setting
COLORS = {'face': (255, 255, 0),
      'NBC': (0, 255, 0),
      'NBC exclusive': (0, 255, 255),
      'voice': (255, 0, 0),
      'flick': (255, 0, 255),
      'clevver news': (255, 255, 255),
      'super woman': (0, 0, 255),
      'marvel': (230, 9, 237)
      }
# train data
female_path = './data/train_data/female/*.jpg'
male_path = './data/train_data/male/*.jpg'
# xml file for haar cascade
face1 = './xml/haarcascade_frontalface_default.xml'
face2 = './xml/mallick_haarcascade_frontalface_default.xml'
profile1 = './xml/haarcascade_profileface.xml'
profile2 = './xml/mallick_haarcascade_profileface.xml'
train_svm = './xml/haarcascade_frontalface_alt_tree.xml'
# logo template file path
LOGO = {'NBC': './Logo/nbc.png',
    'NBC exclusive': './Logo/nbc_exclusive.png',
    'voice': './Logo/the_voice.png',
```

```
    'flick': './Logo/flick.png',
    'twitter': './Logo/twitter.jpg',
    'clevver news': './Logo/clevver_news.png',
    'super woman': './Logo/white_super_woman.png',
    'marvel': './Logo/marvel.png',
    }
# save labeled image
SAVE_PATH = './save/'
CACHE = './cache/'
CLIP_1 = 'clip_1/'
CLIP_2 = 'clip_2/'
CLIP_3 = 'clip_3/'
```