Computer Vision Assignment 5

April 14, 2019

```
In [37]: import cv2
    import numpy as np
    import matplotlib.pyplot as plt
    import glob

plt.rcParams['figure.figsize'] = [14, 12]
```

0.1 Lukcas Kanade Algorithm

The Lucas-Kanade optical flow algorithm is a simple technique which can provide an estimate of the movement of interesting features in successive images of a scene. We would like to associate a movement vector (u, v) to every such "interesting" pixel in the scene, obtained by comparing the two consecutive images.

The Lucas-Kanade algorithm makes some implicit assumptions:

- The two images are separated by a small time increment Δt , in such a way that objects have not displaced significantly (that is, the algorithm works best with slow moving objects).
- The images depict a natural scene containing textured objects exhibiting shades of gray (different intensity levels) which change smoothly.

The Lucas–Kanade method assumes that the displacement of the image contents between two nearby instants (frames) is small and approximately constant within a neighborhood of the point p under consideration. Thus the optical flow equation can be assumed to hold for all pixels within a window centered at p. Namely, the local image flow (velocity) vector (V_x, V_y) must satisfy

$$I_{x}(q_{1})V_{x} + I_{y}(q_{1})V_{y} = -I_{t}(q_{1})$$

$$I_{x}(q_{2})V_{x} + I_{y}(q_{2})V_{y} = -I_{t}(q_{2})$$

$$\vdots$$

$$I_{x}(q_{n})V_{x} + I_{y}(q_{n})V_{y} = -I_{t}(q_{n})$$

where $q_1, q_2, ..., q_n$ are the pixels inside the window, and $I_x(q_i), I_y(q_i), I_t(q_i)$ are the partial derivatives of the image I with respect to position x, y and time t, evaluated at the point q_i and at the current time.

These equations can be written in matrix form Av = b, where

$$A = \begin{bmatrix} I_{x}(q_{1}) & I_{y}(q_{1}) \\ I_{x}(q_{2}) & I_{y}(q_{2}) \\ \vdots & \vdots \\ I_{x}(q_{n}) & I_{y}(q_{n}) \end{bmatrix} \qquad v = \begin{bmatrix} V_{x} \\ V_{y} \end{bmatrix} \qquad b = \begin{bmatrix} -I_{t}(q_{1}) \\ -I_{t}(q_{2}) \\ \vdots \\ -I_{t}(q_{n}) \end{bmatrix}$$

This system has more equations than unknowns and thus it is usually over-determined. The Lucas–Kanade method obtains a compromise solution by the least squares principle. Namely, it solves the 2×2 system

$$A^{T}Av = A^{T}b$$
$$v = (A^{T}A)^{-1}A^{T}b$$

That is, it computes

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum_i I_x(q_i)^2 & \sum_i I_x(q_i) I_y(q_i) \\ \sum_i I_y(q_i) I_x(q_i) & \sum_i I_y(q_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_x(q_i) I_t(q_i) \\ -\sum_i I_y(q_i) I_t(q_i) \end{bmatrix}$$

```
In [2]: def lucas_kadane(frame1, frame2, win = 2):
            Ix = np.zeros(frame1.shape, dtype=np.float32)
            Iy = np.zeros(frame1.shape, dtype=np.float32)
            It = np.zeros(frame1.shape, dtype=np.float32)
            Ix[1:-1, 1:-1] = cv2.subtract(frame1[1:-1, 2:], frame1[1:-1, :-2]) / 2
            Iy[1:-1, 1:-1] = cv2.subtract(frame1[2:, 1:-1], frame1[:-2, 1:-1]) / 2
            It[1:-1, 1:-1] = cv2.subtract(frame1[1:-1, 1:-1], frame2[1:-1, 1:-1])
            params = np.zeros(frame1.shape + (5,))
            params[..., 0] = Ix ** 2
            params[..., 1] = Iy ** 2
            params[..., 2] = Ix * Iy
            params[..., 3] = Ix * It
            params[..., 4] = Iy * It
            del It, Ix, Iy
            cum_params = np.cumsum(np.cumsum(params, axis=0), axis=1)
            del params
            win_params = (cum_params[2 * win + 1:, 2 * win + 1:] -
                          cum_params[2 * win + 1:, :-1 - 2 * win] -
                          cum_params[:-1 - 2 * win, 2 * win + 1:] +
                          cum_params[:-1 - 2 * win, :-1 - 2 * win])
            del cum_params
            op_flow = np.zeros(frame1.shape + (2,))
            det = win_params[...,0] * win_params[..., 1] - win_params[..., 2] **2
            op_flow_x = np.where(det != 0,
                                 (win_params[..., 1] * win_params[..., 3] -
                                  win_params[..., 2] * win_params[..., 4]) / det,
            op_flow_y = np.where(det != 0,
                                 (win_params[..., 0] * win_params[..., 4] -
                                  win_params[..., 2] * win_params[..., 3]) / det,
            op_flow[win + 1: -1 - win, win + 1: -1 - win, 0] = op_flow_x[:-1, :-1]
```

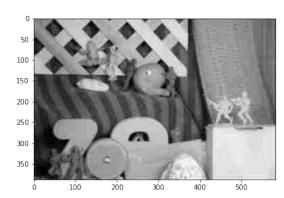
```
op_flow[win + 1: -1 - win, win + 1: -1 - win, 1] = op_flow_y[:-1, :-1]
op_flow = op_flow.astype(np.float32)
return op_flow
```

0.1.1 Draw Flow

Illustration of optical flow on first set of image

Out[11]: <matplotlib.image.AxesImage at 0x7f4c7c5aa8d0>





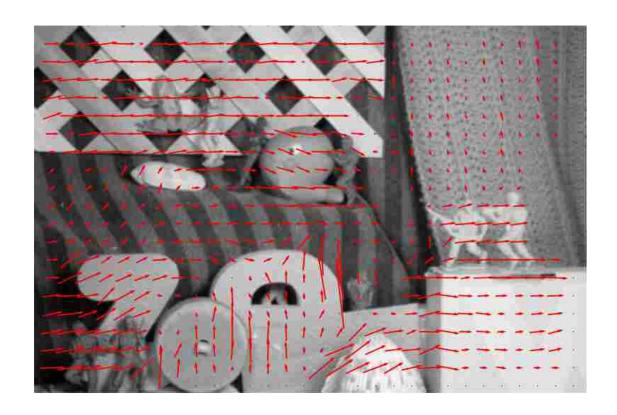
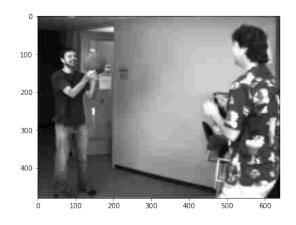
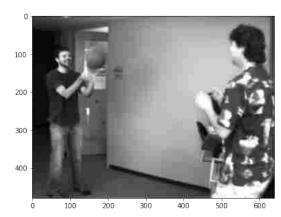


Illustration of optical flow on second set of image

Out[51]: <matplotlib.image.AxesImage at 0x7f6dc38736a0>





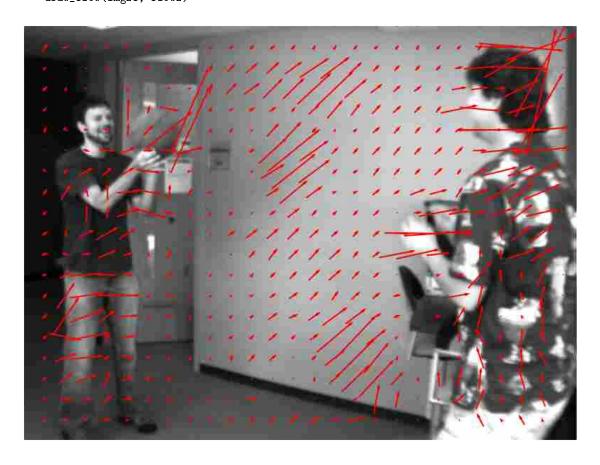


Illustration of optical flow on third set of image

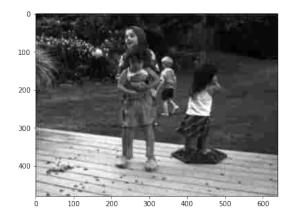
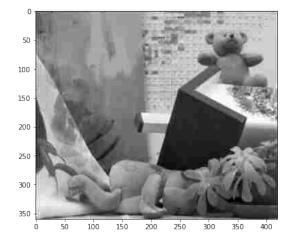


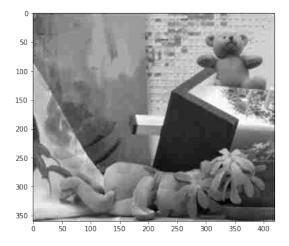




Illustration of optical flow on first set of image

Out[61]: <matplotlib.image.AxesImage at 0x7f6dc329a518>





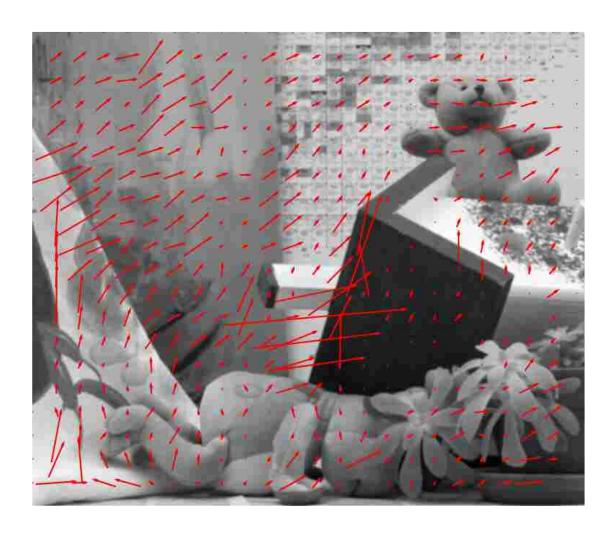
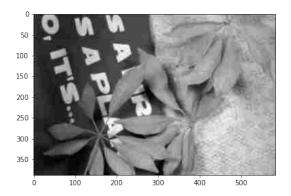
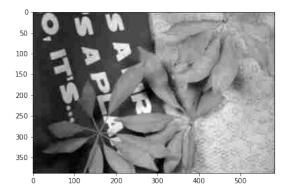
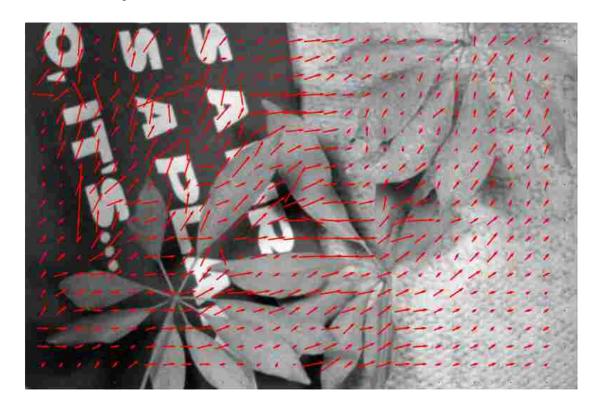


Illustration of optical flow on first set of image







0.2 Optical Flow to detect and segment moving objects in a video frame

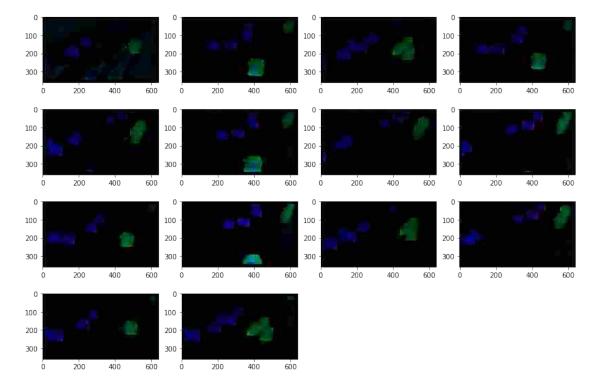
To detect and segment moving objects in a frame, algorithm is: - Find magnitude and angle of flow - Convert hsv[...,0] to ang*180/np.pi/2, where hsv is array with shape of input frame and ang is angle for flow - Convert hsv[...,1] to 255 - Convert hsv[...,2] to normalized magnitude - Convert this hsv to BGR form and return the image

0.2.1 Detect and segment moving objects

```
In [3]: def draw_hsv(flow, img):
    hsv = np.zeros_like(img)
    mag, ang = cv2.cartToPolar(flow[...,0], flow[...,1])
    hsv[...,0] = ang*180/np.pi/2
    hsv[...,1] = 255
    hsv[...,2] = cv2.normalize(mag,None,0,255,cv2.NORM_MINMAX)
    bgr = cv2.cvtColor(hsv,cv2.COLOR_HSV2BGR)
    #cv2.imshow('hsv', bgr)
    return bgr
```

0.2.2 Results

```
In [76]: imageshsv = [cv2.imread(file) for file in glob.glob('output/imagehsv/*.png')]
In [77]: w=10
    h=10
    fig=plt.figure(figsize=(14, 12))
    columns = 4
    rows = 5
    for i in range(0, len(imageshsv)):
        img = np.random.randint(10, size=(h,w))
        fig.add_subplot(rows, columns, i+1)
        plt.imshow(imageshsv[i])
    plt.show()
```



0.3 Optical Flow to track moving objects in a video frame

To track moving objects, the algorithm used is: - Segment the moving object first - Use cv2.threshold to check pixels that has value above cv2.THRESH_BINARY - Dilate this thresh image - Find contour in this threshold image - For each contour if the bounding box has width and height than 15 we draw the bounding box around the moving object

```
In [75]: def track_moving_objects(frame, flow):
              hsv1 = draw_hsv(flow, prev)
              gray1 = cv2.cvtColor(hsv1, cv2.COLOR_BGR2GRAY)
              thresh = cv2.threshold(gray1, 25, 0xFF,
                                         cv2.THRESH_BINARY)[1]
              thresh = cv2.dilate(thresh, None, iterations=2)
              gray2, cnts, hierarchy = cv2.findContours(thresh.copy(), cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
              # loop over the contours
              for c in cnts:
              # if the contour is too small, ignore it
                   (x, y, w, h) = cv2.boundingRect(c)
                  if w > 15 and h > 15 and w < 900 and h < 680:
                           cv2.rectangle(vis, (x, y), (x + w, y + h), (0, 0xFF, 0), 4)
In [78]: imagestrack = [cv2.imread(file) for file in glob.glob('output/imagetrack/*.png')]
In [79]: w=10
         h=10
         fig=plt.figure(figsize=(14, 12))
          columns = 4
          rows = 5
          for i in range(0, len(imagestrack)):
              img = np.random.randint(10, size=(h,w))
              fig.add_subplot(rows, columns, i+1)
              plt.imshow(imagestrack[i])
         plt.show()
      100
                                                       100
                               200
                                                       200
                                                                                200
      200
      300
                                                       300
                           600
                                                    600
                                                                            600
       0
                                                        0
      100
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      300
                           600
                                                    600
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       0
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      100
                               100
                                                       100
      200
                               200
                                                       200
      300
                               300
                                                       300
```

0.4 Analyze how does your algorithm work when camera is moving.

Observation when camera is moving: - The camera movement leads to movement of whole frame captured by the camera - This leads to optical flow being observed in whole frame - Image segmentation isn't that good, because even the background is moving - Tracking foreground moving objects is difficult because even the background is seen moving

0.4.1 Results

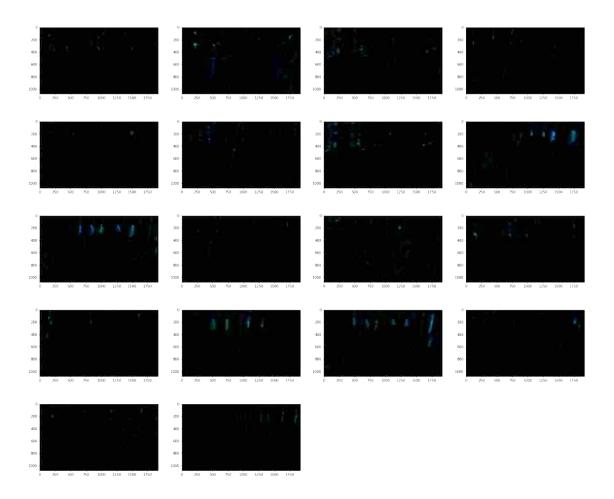
Optical flow

```
In [45]: imagesflow = [cv2.imread(file) for file in glob.glob('output/imageflow/*.png')]
In [51]: w=25
    h=25
    fig=plt.figure(figsize=(28, 24))
    columns = 4
    rows = (len(imagesflow)//4 + 1)
    for i in range(0, len(imagesflow)):
        fig.add_subplot(rows, columns, i+1)
        plt.imshow(imagesflow[i])
    plt.show()
```



Image segmentation

```
In [52]: imageshsv = [cv2.imread(file) for file in glob.glob('output/imagehsv/*.png')]
In [53]: w=25
    h=25
    fig=plt.figure(figsize=(28, 24))
    columns = 4
    rows = (len(imageshsv)//4 +1)
    for i in range(0, len(imageshsv)):
        img = np.random.randint(10, size=(h,w))
        fig.add_subplot(rows, columns, i+1)
        plt.imshow(imageshsv[i])
    plt.show()
```



Tracking moving objects

```
In [62]: imagestrack = [cv2.imread(file) for file in glob.glob('output/imagetrack/*.png')]
In [63]: w=25
    h=25
    fig=plt.figure(figsize=(28, 24))
    columns = 4
    rows = (len(imagestrack)//4 + 1)
    for i in range(0, len(imagestrack)):
        img = np.random.randint(10, size=(h,w))
        fig.add_subplot(rows, columns, i+1)
        plt.imshow(imagestrack[i])
    plt.show()
```



In []: