# Machine Perception Assignment One

Due Date: Week 10 - Monday 5 October 2020 at 5pm

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Abstract—write at this at the end of your report :)
Index Terms—Histograms, I don't know what this is tbh...

#### I. INTRODUCTION

#### do this are the end

II. TASK ONE: IMAGE HISTOGRAM, HARRIS CORNERS AND SCALE-INVARIANT FEATURE TRANSFORM (SIFT) KEY

The Harris corner detection algorithm, and the SIFT algorithm can be thought of algorithms which will pick the key features of an image with the pre-dominate implementations of these algorithms detect the corners of the image [2] [3]. Corners can be thought of as regions in an image with large variation of intensities in all directions [2]. Therefore, the SIFT and the Harris algorithm, are algorithms for detecting the corners in an image the key differences is the invariance and variance to certain image transformations [3]. Harris corner detection algorithm is mainly invariant to rotation, and the SIFT algorithm is mainly invariant to scaling and is also invariant to rotations due the orientation assignment stage of the SIFT algorithm [3], which is explored in greater detail in section IV subsection IV-A.

#### A. Harris corner detection

The Harris corner detection is an algorithm whereby a window function will scan through the image to locate local maximums, these local maximums can be thought as potential candidates for key features detected by the Harris corner detection algorithm [4] [2]. This following behaviour can be modelled by the following equation:

$$E(u,v) = \sum_{(x,y)} w(x,y) [I(x+u,y+v) - I(x,y)]^2$$
 (1)

#### Whereby:

- w(x,y) represents the window which is scanning over each section of the image,
- I(x + u, y + v) represents the intensity neighbouring pixels, and
- I(x,y) represents the intensity of the current pixel.

Thereafter, the function is through taylor expansion to form the following system of equaitons

$$E(u, v) \approx [u \ v]M \begin{bmatrix} u \\ v \end{bmatrix}$$
 (2)

Whereby, M is represented by the following equation

$$M = \sum_{(x,y)} w(x,y) \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix}$$
(3)

Thereafter, a plethora of potential corners are found in the image matrices, the Harris algorithm will then go through each window function to determine if the found corner is most likely going to be an actual corner, this process is determined by the following equation [2]:

$$R = det(M) - k(trace(M))^{2}$$
(4)

Where by det(M) is the multiplication of eigen values of the matrice M, and trace(M) is the addition of the eigen values of the matrice M [2]. Therefore, if one of the eigen values is significantly greater than the other eigen value those found points are most likely to be an edge, and if the eigen vales are large and approximatily the same value that point is a corner otherwise, that point is a flat region [2].

Harris corner detection is an algorithm which can be mainly thought of as a rotation invariant algorithm meaning, no matter the angles you rotate a given image, the algorithm is going to detect the same key-features [2] [4]. This is due to that an corner will always going to remain a corner no matter what orientation the image because a corner is just a high intensity pixel, and the algorithm only looks at a pixel and it's neighbouring pixels thus, no matter what orientation the image the pixels will still have the same neighbouring pixels [2]. Albeit, if you scale the image, a pixels neighbouring pixels will be transformed hence, the window function may determine those clusters of pixels as a non-corner when it's a corner, or as a corner when it's a non-corner. Therefore, the conducted experiments should show consistencies through the set of rotate images, and inconsistencies throught the scaled images.

- B. Harris Corner detection: Results Diamond
  - 1) Rotational Results:
  - 2) Scaling results:
- C. SIFT Results Diamond
  - 1) Rotational results:
  - 2) Scaling results:
- D. Harris Corner detection: Results Dugong
  - 1) Rotational Results:
  - 2) Scaling results:
- E. Discussion about produced resutls

To determine if an image is invariant to a certian transform we have to determine how many corners that image is detecting relative to the performed corners. Hence, the first experiment is to get the returned corners from the Harris corner detector, and the SIFT transform and find the difference relative to the orignal image for each transform. Therefore, for perfect resutls we would assume that the difference should be 0 for invariant feature as they should've picked up the same number of corners in the image. Although, to greater consolidate this claim, we must determine if the corners are been picked up in the same region hence, we calculate the histograms of the image in the same channel as the corners, and theoritically for invariant features the histograms must follow perfectly after each other as the detected pixels should lay in the same region. Finally, to determine how well the histograms follow each other we calculate the distance between each transformed histogram relative to the orignal histogram of the image.

Look at figure 31 we can see that through each rotated image, they is irregularities in the number of keypoints found in each transformed image. It's natrual to conclude that this experiment dis-prove harris corner detection invariance to rotatin. Albiet, we have to consider the manner the image is rotated. As can be seen in figures 32, 33, 34, and 35 you can see when you rotate the image they is an increase of black space around the iamge, and the boarders of the image may have been picked up as a corner. In figure 32 you see the boarders of the image are detected as a corner but, in the other images the boarders are not detected as a corner. Therefore, with this observation we should expect irregularties in the data produced. Furthermore, revisting figure 31 we can see the produced histograms follow a clear sinusoidal pattern implying that although they is irregularty between the number of corners found in each transformed image but atleast they is consistency of the number of corners found relative to the angle of rotation of the image. Therefore, we can infer that the harris corner detection algorithm would produce the same number of corners if each rotated image had a tightly bounded box around the image thus removing the corners picked up by the boarders of the image. Therefore, encounting for the extra corners found due to the boarders of the image we can infer that the number of corners found for each transformed image will be very similiar to the original transformed image. This

same concepts will apply for the images found in the dugong images in section??.

Looking, at the scaled results of the experiment we will expect the same to hold for invarinat properties for the image, and the opposite to be true for variance to a specific image transform. Therefore, we should be expecting no clear pattern in the produced histograms for the first experiement, we should see great irregularity in the produced histograms, and we should see great irregularity in the distances betweeen the produced histograms. Therefore, as seen in figures 8,

#### III. I AM HERE EDITING

Encounting only for the numbers of corners found by the harris corner detection is not enough to proove the invariance of the algorihm. For the diamond playing card the only two visible colors are white, and red hence we can use the cards characterisitic to our advantage by drawing the found corners in the green channel, the same can be said about the dugong image by drawing the found corners onto the red channel as seen in section II-B. The aim of this experiment to see if the found corners are going to be laying in the same color space as the original image hence, for the playing card we should get a spike of green pixels around the cluster of red pixels. Referring, to figure 37 we can see that the histograms overlay over each other for the mid intensities, and they is some deviation in the lower intensities. Divation in the lower intensities of the image is expected as in some transformed images we're introducing more black pixels into the image because of the method we're using to rotate the image as seen 32, 33, 34, and 35. Therefore, as we can see the produced histogramms in figure 37 support the invariance of the harris corner detection.

Furthermore, this is further considolated through the caclulated distances between the transformed image, and the original image. As we can see in figure 31 the distances found in each transformed image is the same. Given, the introduction of greater quantity of black pixels due to the manner of rotation of the image we would expect the histograms to be a fixed distance away from eah other which, is demonstrated through figure 31. Therefore, as demonstrated the harris corner detection rotationall invariant as show through the diamond card.

#### IV. TASK TWO: IMAGE FEATURES

an example on how to refernce other sections V

A. part ii

# V. TASK THREE

A. Results for Diamond playing card

Don't forget to include the areas found by each object extracted

Don't forget to insert the tables for the area found for each object in here as well

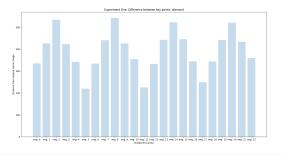


Fig. 1: Difference of keypoitns found relative to first image: Harris, Rotated, Diamond

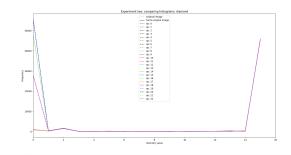


Fig. 2: Comparison of histograms for each transformed image: Harris, Roateted, Diamond

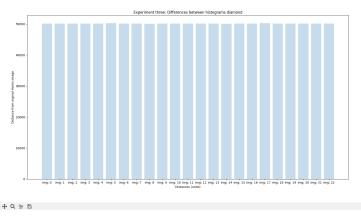


Fig. 3: Difference of distances between histograms relative to orignal: Harris, Rotated, Diamond

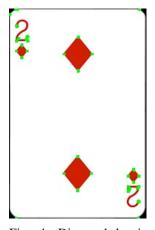


Fig. 4: Diamond harris rotated original produced image

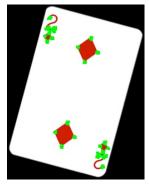


Fig. 5: Diamond harris image 1 rotated produced image

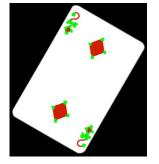


Fig. 6: Diamond harris image 2 rotated produced image

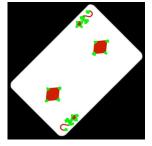


Fig. 7: Diamond harris image 3 rotated produced image

# B. Results for Dugong

don't forget to insert the results for the area found by the algorithm

don't forget to insert to insert the resutls for the area

found by the algorithm here

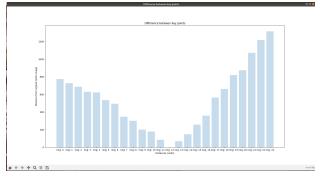


Fig. 8: Difference of keypoitns found relative to first image: Harris, Scaled, Diamond

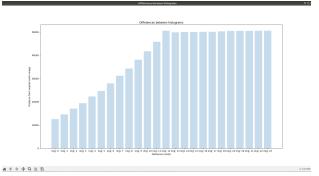


Fig. 9: Difference between the distances of histograms: Harris, scaled, Diamond

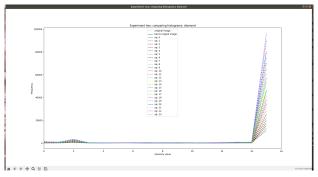


Fig. 10: All produced histgrams: Harris, Scaled, Diamond

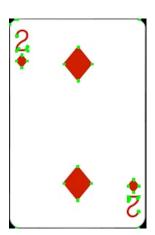


Fig. 11: Harris scaled orignal produced image: Harris, Scaled, Diamond

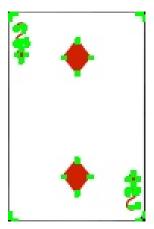


Fig. 12: Diamond arris image 1 scaled produced image

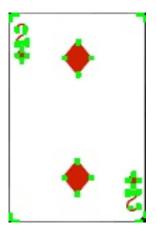


Fig. 13: Diamond harris image 2 scaled produced image

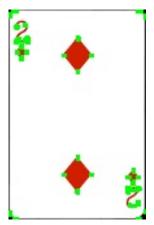


Fig. 14: Diamond harris image 3 scaled produced image

# VI. TASK FOUR: IMAGE SEGMENTATION WITH K-MEANS

A. Diamond: Image Segmentation: with HSV color space

B. Diamond: Image Segmentation: with BGR color space

C. Diamond: Image Segmentation: with contouring

# VII. SEPERATE HERE

A. Dugong: Image Segmentation: with HSV color space B. Dugong: Image Segmentation: with BGR color space

C. Dugong: Image Segmentation: with contouring

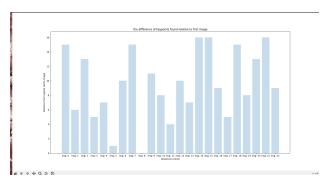


Fig. 15: Difference of keypoitns found relative to first image: SIFT, Rotated, Diamond

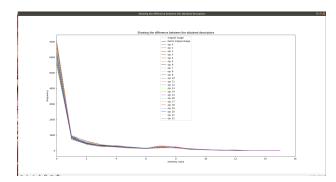


Fig. 16: Comparison of histograms for each transformed image: SIFT, Roateted, Diamond

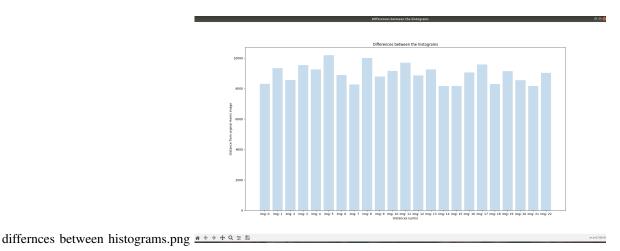


Fig. 17: Difference of distances between histograms relative to orignal: SIFT, Rotated, Diamond

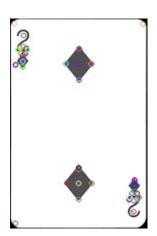


Fig. 18: Diamond SIFT rotated original produced image

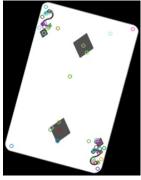


Fig. 19: Diamond SIFT image 1 rotated produced image



Fig. 20: Diamond SIFT image 2 rotated produced image

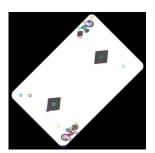


Fig. 21: Diamond SIFT image 3 rotated produced image

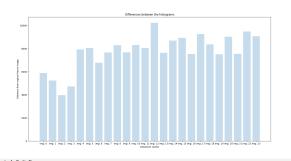


Fig. 22: Difference of keypoitns found relative to first image: SIFT, Scaled, Diamond

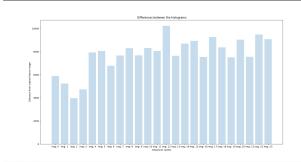


Fig. 23: Difference between the distances of histograms

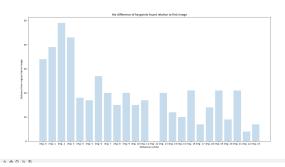


Fig. 24: All produced histgrams: SIFT, Scaled, Diamond

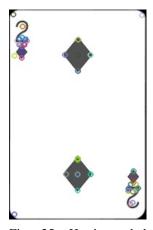


Fig. 25: Harris scaled orignal produced image: Harris, Scaled, Diamond

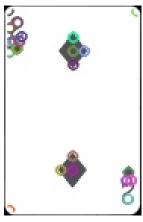


Fig. 26: Diamond SIFT image 1 scaled produced image

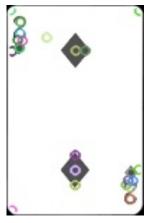


Fig. 27: Diamond SIFT image 2 scaled produced image

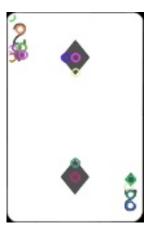


Fig. 28: Diamond SIFT image 3 scaled produced image

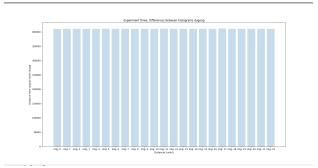


Fig. 29: Difference of keypoints found relative to first image: Harris, Rotated, Diamond

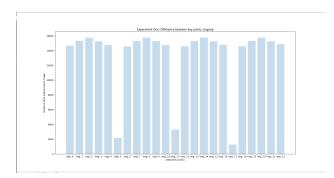


Fig. 30: Comparison of histograms for each transformed image: Harris, Roateted, Diamond

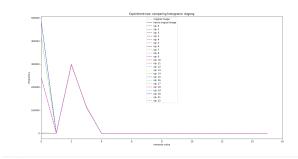


Fig. 31: Difference of distances between histograms relative to orignal: Harris, Rotated, Diamond



Fig. 32: Diamond harris rotated original produced image

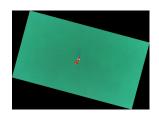


Fig. 33: Diamond harris image 1 rotated produced image

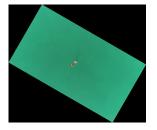


Fig. 34: Diamond harris image 2 rotated produced image

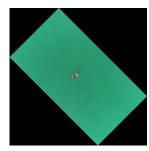


Fig. 35: Diamond harris image 3 rotated produced image

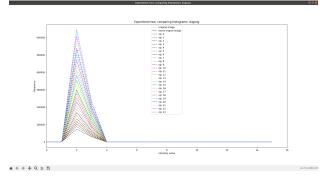


Fig. 37: Comparison of histograms for each transformed image: Harris, Roateted, Diamond

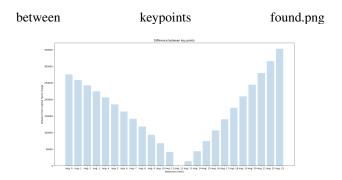


Fig. 36: Difference of keypoitns found relative to first image: Harris, Rotated, Diamond

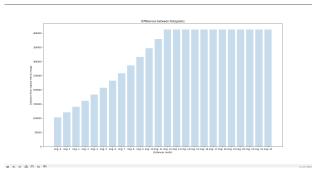


Fig. 38: Difference of keypoitns found relative to first image: Harris, Rotated, Diamond



Fig. 39: Diamond harris scaled original produced image



Fig. 40: Diamond harris image 1 scaled produced image



Fig. 41: Diamond harris image 2 scaled produced image



Fig. 42: Diamond harris image 3 scaled produced image

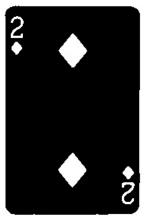


Fig. 43: Diamond: Seperated fore-ground and background



Fig. 44: Diamond: the labelling of each object found in the image



Fig. 45: Dugong: Seperated fore-ground and background

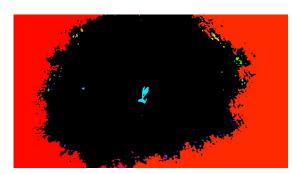


Fig. 46: Dugong: the labelling of each object found in the image

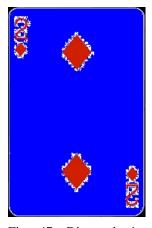


Fig. 47: Diamond: 1st cluster found by k-means

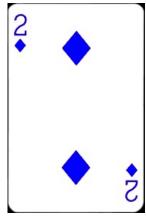


Fig. 48: Diamond: 2nd cluster found by k-means

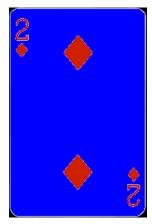


Fig. 49: Cluster found by the BGR color space

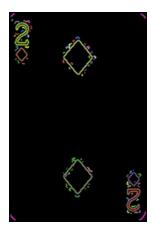


Fig. 50: Image segmentation done by contouring



Fig. 51: Dugong: 1st cluster found by k-means

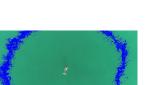


Fig. 54: Dugong: 1st cluster found by k-means

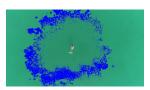


Fig. 52: Dugong: 2nd cluster found by k-means

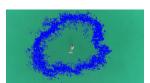


Fig. 55: Dugong: 2nd cluster found by k-means



Fig. 53: Dugong: 3rd cluster found by k-means



Fig. 56: Dugong: 3rd cluster found by k-means

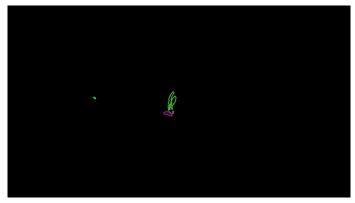


Fig. 57: Dugong: Image segmentation done by contouring

### REFERENCES

- [1] Dr. S. An. 2020. Machine Perception Lecture 03 [PowerPoint slides] Available:https://learn-ap-southeast-2-prod-fleet01-xythos.s3.ap-southeast-2.amazonaws.com/5dc3e34515a0e/4348643?response-cache-control=private%2C%20max-age%3D21600&response-content-disposition=inline%3B%20filename%2A%3DUTF-8%27%27lecture03\_feature\_detection.pdf&response-content-type=application%2Fpdf&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Date=20200927T060000Z&X-Amz-SignedHeaders=host&X-Amz-Expires=21600&X-Amz-Credential=AKIAYDKQORRYZBCCQFY5%2F20200927%2Fap-southeast-2%2Fs3%2Faws4\_request&X-Amz-Signature=bcf107d5e76759efe45687b516ac725158189de0af558d0a7a798df1723f4299
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- [3] . OpenCV. "Introduction to SIFT (Scale-Invariant Feature Transform)". OpenCV-Open source Computer vision. https://docs.opencv.org/3.4/da/df5/tutorial\_py\_sift\_intro.html
- [4] . C. Harris and M. Stephens. 1988. A Combined Corner And Edge Detector. Plessey Reasearch Roke Manor, UK. [Online]. Available: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.434.4816&rep=rep1&type=pdf

**APPENDIX** 

APPENDIX A
TASK 1 CODE PRINT OUT
APPENDIX B
TASK 2 CODE PRINT OUT