Homework 2 Written Questions

CSCI 1430

Template Instructions

This document is a template with specific answer regions and a fixed number of pages. Given large class sizes and limited TA time, the template helps the course staff to grade efficiently and still focus on the content of your submissions. Please help us in this task:

- Make this document anonymous.
- Questions are in the orange boxes. Provide answers in the green boxes.
- Use the footer to check for correct page alignment.
- **Do NOT remove the answer box.**
- **Do NOT change the size of the answer box.**
- **Extra pages are not permitted unless otherwise specified.**
- **Template edits or page misalignment will lead to a 10 point deduction.**

Gradescope Submission

- Compile this document to a PDF and submit it to Gradescope.
- Pages will be automatically assigned to the right questions on Gradescope.

This Homework

- 5 questions **[10 + 4 + 9 + 10 + 10 = 43 points]**.
- Include code, images, and equations where appropriate.

Q1 — [10 points]

Let's look at the Fourier transform demo from class. The Fourier transform lets us operate on images with respect to their frequency content via the **amplitude** (or magnitude) and the **phase**. From your uv environment, run these commands:

```
$ uv pip install dearpygui
$ cd questions/fourierdemo
$ uv run python liveFourier.py
```

Play with the demo! To consider the properties of the Fourier domain, it will help to use 'Cat Mode' so that we see a fixed image (of a cat).
Then, for each transform listed in the rows below, please place ■ in the columns that best describe the effects. There may be multiple for each row, or none.

- In the demo, you may see minor changes in amplitude/phase due to image resampling, quantization, and clipping; try to ignore these and think about the **fundamental properties**: what should happen to amplitude and phase?
- I represents the image intensity, x represents the image's pixel coordinates.
- "DC only" means effect is only on zero-frequency component (DC offset).
- "Scales same" means shrinks when the input shrinks; "Scales inverse" means expands when input shrinks.

Input transform	**Invariant**	**Intensity increases**	**DC only**	**2D translates**	**2D rotates**	**2D scales same**	**2D scales inverse**
Change intensity ($I+=0.2$)							
Effect on amplitude	☐	☐	☐	☐	☐	☐	☐
Effect on phase	☐	☐	☐	☐	☐	☐	☐
Change intensity ($I*=1.2$)							
Effect on amplitude	☐	☐	☐	☐	☐	☐	☐
Effect on phase	☐	☐	☐	☐	☐	☐	☐
2D translate ($x+=20$)							
Effect on amplitude	☐	☐	☐	☐	☐	☐	☐
Effect on phase	☐	☐	☐	☐	☐	☐	☐
2D rotate (x by $45°$)							
Effect on amplitude	☐	☐	☐	☐	☐	☐	☐
Effect on phase	☐	☐	☐	☐	☐	☐	☐
2D scale ($x*=0.5$)							
Effect on amplitude	☐	☐	☐	☐	☐	☐	☐
Effect on phase	☐	☐	☐	☐	☐	☐	☐

Q2 — [4 points]

In class, we saw another demo that connected the Fourier domain to convolution.

```
$ uv run python liveConvolutionTheorem.py
```

Play with the demo!
In your own words, what is the connection between the Fourier domain and convolution, and what benefits can it provide? **[3-5 sentences]**

TODO: Your answer here

Often in computer vision, we wish to find points in one image that match to the same world point in another image—so-called correspondence finding.

Q3 — [9 points]

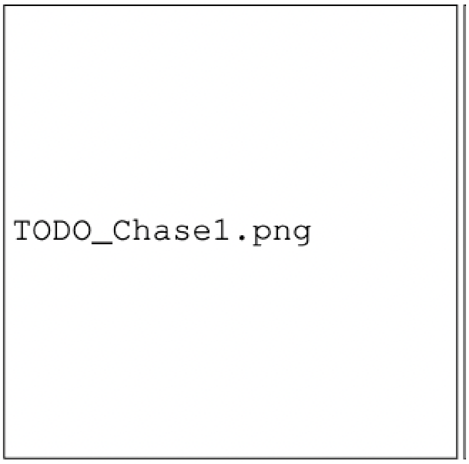
In the following three pairs of images, please use the included python script `plot_corners.py` to find corners using the Harris corner detection algorithm. Run the script with `python plot_corners.py {example}` where `{example}` is one of {`RISHLibrary`, `Chase`, `LaddObservatory`}. For each pair, discuss any differences in the returned corners, the properties of the images that create these differences, and any underlying real world phenomena that may have been the primary cause of these differences. **[3–5 sentences]**

RISHLibrary: [3 points] RISHLibrary1.jpg and RISHLibrary2.jpg

TODO_RISHLibrary1.png

TODO: Your answer here

Chase: [3 points] Chase1.jpg and Chase2.jpg



TODO: Your answer here

LaddObservatory: [3 points] LaddObservatory1.jpg and LaddObservatory2.jpg

TODO: Your answer here

Q4 — [10 points]
As we just saw, the Harris Corner Detector can find feature points for image matching.

To detect these features, the algorithm approximates the strength of any change in the windowed auto-correlation function $E(u, v)$ over shifts u, v. We look at the second derivative term in the Taylor series expansion of E to consider the local shape of $E(u, v)$ via the *structure tensor* M (often also called the second moment matrix).

$$M = \sum_{(x,y)\in W} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

where w is typically a Gaussian window function. Then, we analyze M to determine if that pixel is a corner or not.

Note: This question requires careful study and a precise answer.

Q4.1 — [3 points]

Consider the spatial derivatives I_x and I_y at each pixel in the window W. Suppose we plotted these (I_x, I_y) values as points in a 2D scatter plot. Describe the shape or distribution of the points that would form for (i) a flat region, (ii) an edge, and (iii) a corner. **[3–5 sentences]**

TODO: Your answer here.
(i)
(ii)
(iii)

Q4.2 — [3 points]

Suppose we consider the eigendecomposition of the structure tensor M. How do the eigenvalues of M relate to the local image intensity patterns, and how might we interpret the eigenvalues geometrically as an ellipse? **[6–8 sentences]**

TODO: Your answer here.

Q4.3 — [4 points]

M is constructed using image derivatives I_x and I_y from the horizontal and vertical axes. We know that real-world edges are rarely axis-aligned, yet the Harris detector is rotationally invariant. Mathematically, why does Harris' cornerness response function

$$R = det(M) - \alpha(trace(M))^2$$

have this rotation invariance property **without** needing to perform a factorization of M, i.e., via eigendecomposition to find the principal directions (eigenvectors)?

TODO: Your answer here.

Q5 — [10 points]

One use of local feature description and matching is fingerprint recognition—please watch the video and note the similarity to our task in this homework.

Fingerprint recognition uses biometric data—measurements of human biological features that are unique to an individual—to unlock doors or devices quickly and without needing to remember a password. However, given its uniqueness, biometric data may be seen as a greater privacy encroachment upon a person than a password. Further, given the trust that is derived from the uniqueness of biometric data, it may also pose a greater risk of misuse if the data is not secure because the data cannot be changed.

Q5.1 — [3 points]

Do you use biometric recognition systems? List them. [If not, list some that people around you use.]
For one of the systems you use, where is the reference data stored (such as your stored fingerprint), where does the authentication happen, and how does the authentication happen (at a high level)? If you don't know, then try to find the answer online. **[4–6 sentences]**

TODO your answer here.

Brown University decides to entirely replace passwords with biometric data to authenticate student identity on its computer systems. Given how accurate your feature matching homework 2 code is, Brown asks you to develop the authentication system as your CSCI 1430 final project. Lucky you.

In preparation, you read a previous case about a biometric data breach.
(See **BioStar2_DataBreach.md**)

Q5.2 — [3 points]

How were BioStar 2 storing their fingerprint data? Knowing the computer vision algorithms involved in feature matching, what different processing, features, or storage might you consider instead to decrease the risk of a biometric data breach? **[4–6 sentences]**

TODO: Your answer here.

Q5.3 — [4 points]
Even though fingerprints are thought to be unique, we are bound by the accuracy of computer vision systems to detect and recognize that uniqueness. This may be a challenge for Brown's 10,000 students, let alone a national-scale database such as the FBI's Next Generation Identification System that houses around 190 million prints and conducts 170,000 daily assessments (Jan. 2026; see **NGI_Jan2026_SystemFactSheet.pdf**). NGI's Advanced Fingerprint Identification Technology is claimed to be 99.6% accurate.

Even seemingly high accuracies can create many inaccurate matches with large databases, potentially causing inaccurate judgements in criminal cases.

Fingerprint images are quite different from the images of natural 'human-scale' scenes we've been using throughout the course. Is correspondence finding for fingerprint images an easier problem than for natural images? Why or why not? Think about the variation within each domain of images, the accuracy required, the consequences of a match (or lack thereof), the accuracy required, and the scope of the application. **[6–8 sentences]**

Feel free to refer to the video at the beginning of Q3, and for more detail please refer to the first 15 slides of this deck—it has example fingerprints and additional information.

TODO: Your answer here.

Only Q5.3 should be on this page

Feedback? (Optional)

We appreciate your feedback on how to improve the course. You can provide anonymous feedback through this form which can be accessed using your Brown account (your identity will not be collected). If you have urgent non-anonymous comments/questions, please email the instructor.