Assignment - 4.3

The primary objective of this project is two-fold:

Computing H and b without For-Loops: Develop Python functions to compute the matrix H and vector b without using for-loops and validate their correctness using synthetic data.

Sensitivity to Outlier Matches: Investigate the impact of the number of matches and the presence of outliers on the estimation of transformation parameters between images.

1. Computing H and b without For-Loops

In the first part of this assignment, I computed the matrix H and vector b without leveraging for-loops. This demanded a shift in approach, I focused on NumPy's broadcasting and vectorization capabilities to perform calculations in a more efficient way.

Function Definitions
compute_H(X, Y): This function returns a 2x2 matrix H calculated using numpy arrays X and Y, representing corresponding x and y values in the sample data.

compute_b(X, Y): This function computes and returns a 2x1 matrix b utilizing numpy arrays X and Y.

Both X and Y are numpy arrays of size N by 1, storing the x and y values in correspondence order; X[i] is associated with Y[i].

Synthetic Data and Parameter Estimation
To validate the functions, synthetic data was generated using a known noisy model, and the parameters were estimated. The functions were tested extensively to ensure their accuracy. Using synthetic data generated using a known linear model with noise.

The true values of a and b are 2.5 and 1.0, respectively.

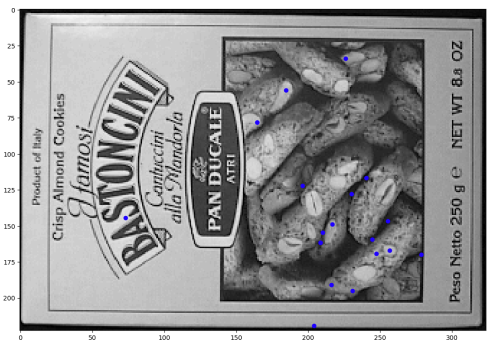
Creating synthetic data to validate the approach was a crucial step. It not only provided a means to ensure the correctness of the developed functions but also offered insights into the impact of noise on parameter estimation. The ability of the least squares method to yield accurate parameter estimates even in the presence of noise was a significant learning outcome from this experiment.

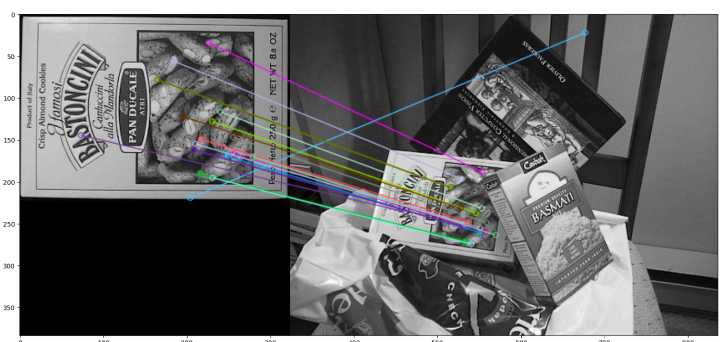
2. Sensitivity to Outlier Matches

The subsequent phase involved examining the sensitivity of the matching process to outlier matches. The exploration was performed using SIFT features, and the matches were obtained through the BFMatcher in OpenCV. Different numbers of matches, specifically 10, 15, and 20, were considered to study the variations and implications.

Handling Outliers
In the presence of outliers, the estimation can be inaccurate. I opted to use the RANSAC algorithm to estimate the affine transformation parameters between images, to reduce the impact of outliers. The algorithm uses matched SIFT features between the images as point

correspondences. RANSAC (Random Sample Consensus) is a widely used method to estimate parameters of a mathematical model from a set of observed data that contains outliers. Its randomly selects a subset of the data and fits the model to this subset. Then it classifies data points as inliers or outliers based on how well they fit the model. Finally it re-estimates the model using the inliers. In this second part of the assignment I directed my focus towards understanding the implications of outliers on parameter estimation, particularly in the context of image transformations. Here, the exploration of the RANSAC algorithm opened up new perspectives for me on the resilience and adaptability of estimation algorithms in handling outliers. It was fascinating to observe how, through iterative model estimation and inlier classification, RANSAC could determine transformation parameters even when the data was polluted with incorrect matches.





The number of matches, NUM_MATCHES, is varied among [10, 15, 20] to observe the effect on the estimation results.

When NUM_MATCHES is increased, the chance of incorporating more outlier matches is higher. This could potentially affect the accuracy of the estimated transformation.
The residual error is an essential factor to consider, as it gives insight into the quality of the fit.
A lower residual error indicates a better fit and vice versa.

Results and Observations

1. Computing H and b without For-Loops

The estimated parameters were in close agreement with the true parameters, establishing the accuracy of the compute_H and compute_b functions. The functions were efficient and could handle noisy synthetic data effectively.

Computed H: [[14 6] [6 3]]
Computed b: [[14] [6]]

Estimated Parameters:
Estimated a: 2.4990296233752423
Estimated b: 1.007716724932393

True Parameters:
True a: 2.5
True b: 1.0

2. Sensitivity to Outlier Matches

Varying the number of matches had a big impact on the residual error. The RANSAC algorithm proved instrumental in handling outliers and provided reliable estimations of transformation parameters.

The number of matches, NUM_MATCHES, was varied, and I observed the effect on the residual error. I found a correlation between the increase in matches and the augmentation of errors, indicative of the presence of outlier matches. The exploration demonstrated the crucial role of algorithms like RANSAC in computer vision, specifically in situations where the sensitivity to outlier matches can profoundly impact the results.

Conclusions and Recommendations

The development and validation provided insights into the computation of transformation parameters using matrix operations without for-loops, making the computation efficient. compute_H and compute_b, successfully compute the matrix H and vector b efficiently and accurately. The synthetic data experiment validated the correctness of the implemented functions against noise.

The sensitivity analysis highlighted the significance of the number of matches and the effectiveness of estimation techniques like the RANSAC algorithm in mitigating the impact of outliers. RANSAC proved to be effective in estimating affine transformation parameters even in the presence of outlier matches.