RBE 549 Computer Vision
HW1 -AutoCalib

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***Abstract*—Camera calibration is a fundamental aspect of computer vision. In this assignment, we focus on calibrating a camera by determining its intrinsic and extrinsic parameters. Our approach is based on Zhengyou Zhang's camera calibration technique. Subsequently, we aim to optimize the error between the actual points and the points obtained after distortion correction.**

***Index Terms*—Camera Calibration, Intrinsics, Extrinsics, Distortion, Reprojection**

I. Introduction

This report delves into camera calibration techniques, with a particular focus on Zhengyou Zhang's method, which amalgamates traditional photogrammetric and self-calibration principles. Zhang's approach leverages 2D metric information, providing enhanced flexibility compared to conventional methods and increased robustness over self-calibration. This robustness results from constraints imposed on the camera's intrinsic parameters, as inferred from single-plane observations. The primary objective is to compute vital calibration parameters by employing images of a chessboard captured by a specific camera and subsequently comparing them to a 2D representation of the chessboard. The calibration process involves two transformation matrices: one for mapping real-world coordinates to the image plane (extrinsic parameters) and another for mapping image plane coordinates to pixel coordinates (intrinsic parameters).

II. Initial Parameter Estimation

For this assignment, we utilized thirteen images taken with a Google Pixel XL phone with a locked focus setting. Each square on the chessboard measured 21.5mm per side, forming a grid of 10x7 squares (X and Y axes). We employed the `cv2.findChessboardCorners()` function to detect the chessboard corners in all images. Subsequently, we calculated the homography (H) between these corners using `cv2.findHomography()`, comparing them with the world coordinate corners from the calibration target (a 2D flat representation of the same chessboard).

The camera calibration process relies on several assumptions and approximations to ensure simplicity and efficiency.

A. Camera Intrinsics

Using the previously calculated homography matrix (H), we derived the camera intrinsic matrix (K) through a closed-form solution, as outlined in the provided paper. The K matrix is represented as:

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

Where:

f_x, f_y : Focal lengths (x and y-directions)

c_x, c_y : Principal point offsets (x and y-directions)

B. Camera Extrinsics

Building on the K matrix and its parameters, along with the previously obtained homography data, we proceeded to compute the camera extrinsics. These include the Rotation (R) and translation (t) vectors, which together form the transformation matrix.

C. Distortion Model

In our analysis, we assumed minimal camera distortion, specifically setting $k = [0, 0]^T$ as an initial estimate. We considered radial distortion parameters k_1 and k_2. Here, (u,v) represents ideal pixel coordinates without distortion, while (x,y) denotes ideal normalized image coordinates without distortion.

III. Optimization

In the calibration process, after obtaining initial estimates of the camera matrix K, rotation matrices R, translation vectors t, and distortion parameters k, we proceed to refine these parameters using non-linear optimization. The goal is to minimize geometric error through Maximum Likelihood Estimation (MLE). MLE aims to improve the parameter estimates by minimizing the discrepancy between the observed corner coordinates in the image and the reprojected corner coordinates obtained from the estimated parameters.

To define a more accurate model, we update the distortion parameters alongside the intrinsic and extrinsic parameters. The MLE problem is formulated to minimize the error across all observations and is given by the following functional:

$$\sum_{i=1}^{N} \sum_{j=1}^{M} \left\| \mathbf{x}_{ij} - \hat{\mathbf{x}}_{ij}(K, R_i, t_i, X_j, k) \right\|^2, \qquad (1)$$

where $\mathbf{x}_{ij}$ are the observed image corner coordinates, and $\hat{\mathbf{x}}_{ij}$ are the projected coordinates using the estimated camera parameters.

The optimization is carried out using the `scipy.optimize.least_squares` function from the SciPy library, which implements the Levenberg-Marquardt algorithm, a robust method for solving non-linear least squares problems.

After optimization, the refined camera parameters are obtained. For example, the optimized camera matrix K and distortion coefficients vector k may look like the following:

$$K = \begin{bmatrix} 2464.4 & -0.368 & 763.8 \\ 0 & 2444.1 & 1348.3 \\ 0 & 0 & 1 \end{bmatrix}, \quad k = \begin{bmatrix} 0.0125 \\ -0.0125 \end{bmatrix}. \quad (2)$$

The reprojection error provides a quantitative measure of the optimization's effectiveness. For instance, the reprojection error might be 0.7535, indicating the average distance between the observed and projected points in pixel units.

A. Results

Initial K matrix:

$$\begin{bmatrix} 2.05468167e+03 & 1.86528233e+00 & 7.53082837e+02 \\ 0.00000000e+00 & 2.04041395e+03 & 1.35021724e+03 \\ 0.00000000e+00 & 0.00000000e+00 & 1.00000000e+00 \end{bmatrix}$$

Initial RMS Projection Estimate: 0.7647392609865468

Final K matrix:

$$\begin{bmatrix} 2.05467900e+03 & 1.86608678e+00 & 7.53086896e+02 \\ 0.00000000e+00 & 2.04041012e+03 & 1.35023470e+03 \\ 0.00000000e+00 & 0.00000000e+00 & 1.00000000e+00 \end{bmatrix}$$

Final Distortion matrix:

$$\begin{bmatrix} 0.01423685 \\ -0.10394231 \end{bmatrix}$$

Final RMS Projection Estimate: 0.7419044459339967

Through the calibration process outlined, significant enhancements were achieved in determining precise camera intrinsic parameters, leading to enhanced accuracy in image projection and distortion correction, as evidenced by the reduction in the root mean square (RMS) projection estimate from the initial to final stages.

References

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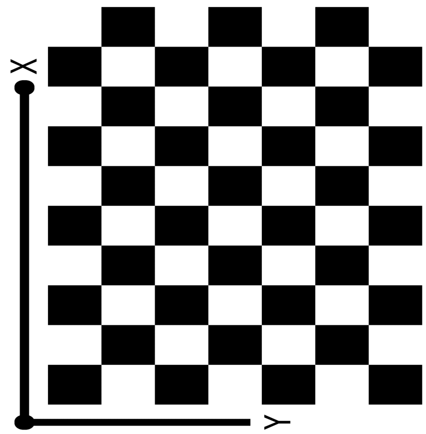

Fig. 1. Calibration Target Image (World)

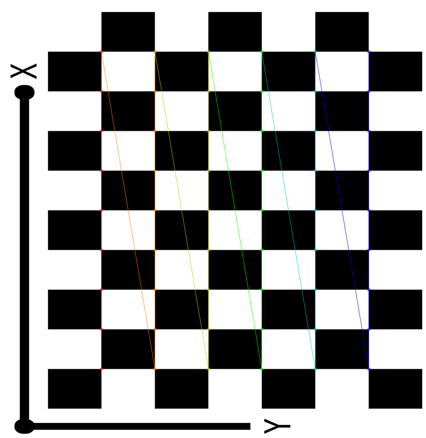

Fig. 2. World Image with detected corners

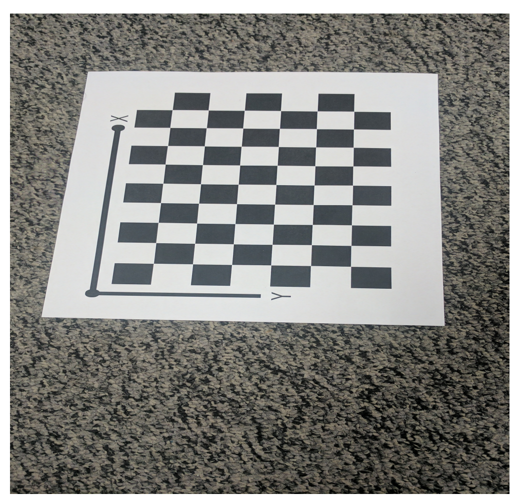

Fig. 3. Captured Original Image

Fig. 4. Image pair 1

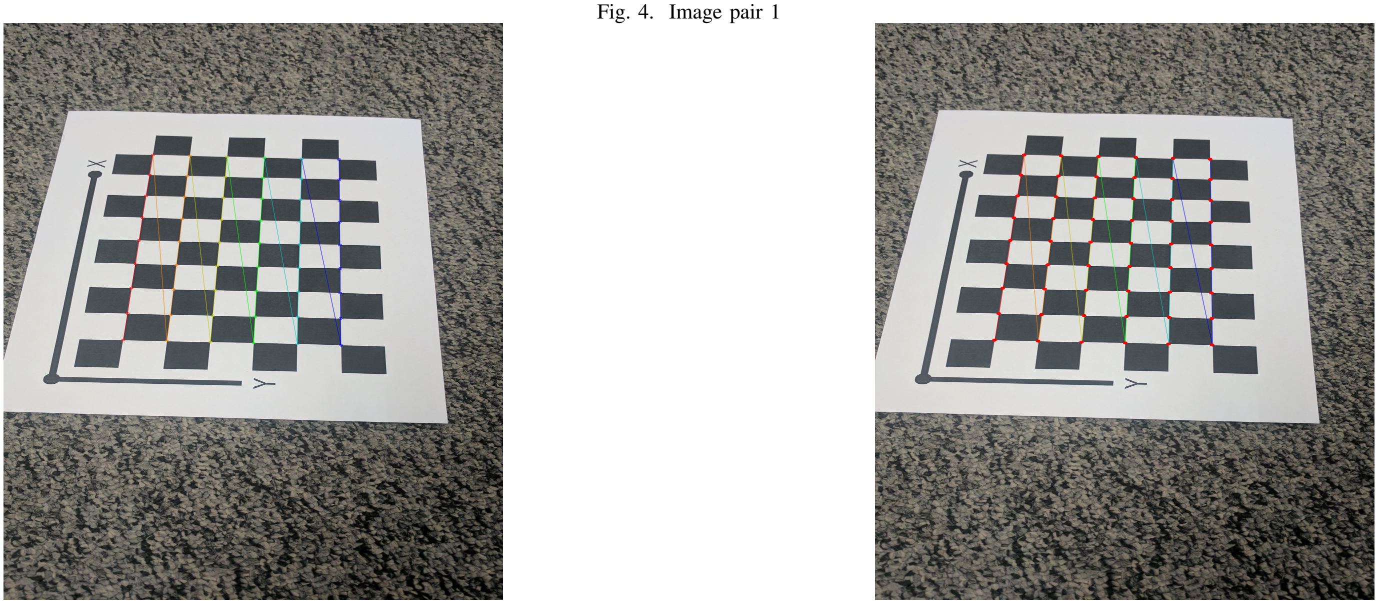

Fig. 5. Image pair 2

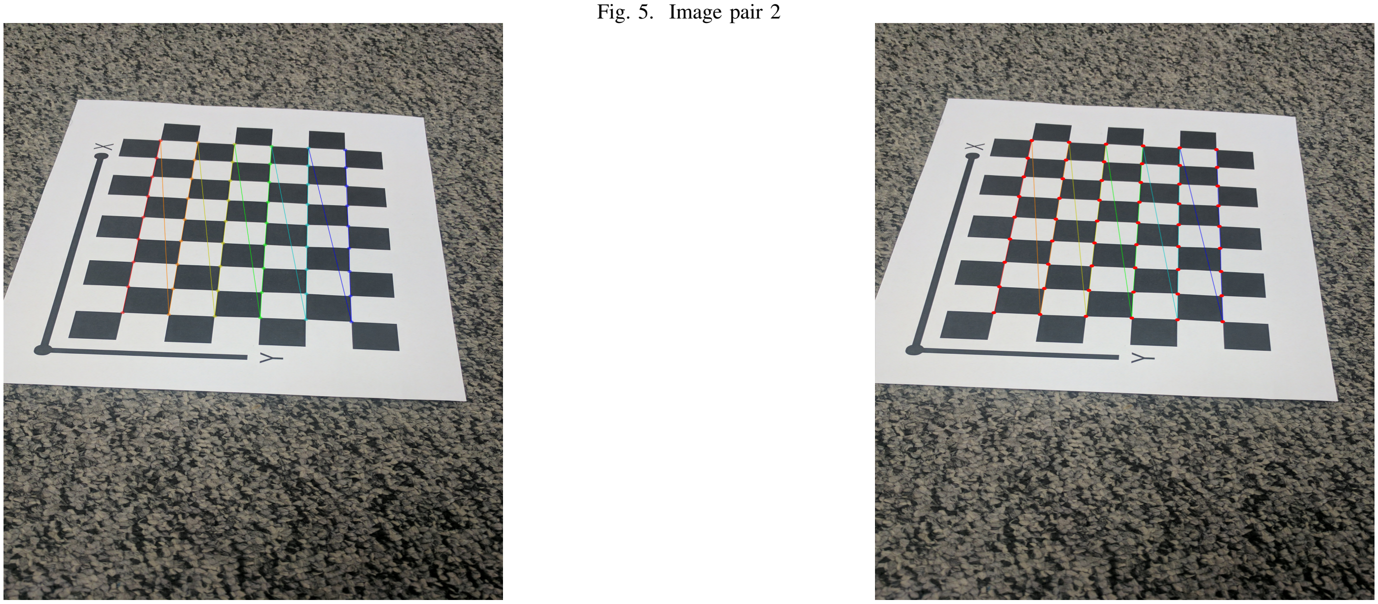

Fig. 6. Image pair 3

Fig. 7. Images before and after Optimization