# Team28 : Image Stitching with Chessboard

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## 1 Introduction

This project was inspired by our classroom assignments. We aim to extend and combine ideas from various tasks to explore how to use chessboard markers for image stitching. In the assignments, we learned how to perform camera calibration using chessboards and how to process images with basic techniques. Building on this foundation, we have developed the following workflow:

1. **Capturing and Marking** : During photo capturing, we use a chessboard as a marker to help determine the camera's spatial position and orientation.

2. **Back-Projecting Image Relations**: By back-projecting the camera's shooting positions, we explore how to align the spatial relationships of multiple images.

3. **Experimenting with Different Stitching Methods**: Instead of sticking to a single method, we experiment with various image stitching techniques to combine multiple photos into a complete image.

This project emphasizes the integration of creativity and learning. By extending the knowledge gained in class, we explore more possibilities in image processing.

## 2 Approach

### 2.1 Capturing and Marking

We begin by manually selecting the center point of the chessboard in each photo and recording its pixel coordinates. Based on the selected center point, we extend 135 pixels in all directions (up, down, left, and right) to crop the region containing the chessboard, resulting in localized images of the chessboard. This process ensures that the chessboard in each photo is clearly extracted, providing accurate input data for subsequent corner detection. During cropping, special care is taken to ensure that the entire chessboard is within the cropped region; otherwise, it may affect the performance of the following steps.

Figure 1: Image with chessboard

### 2.2 Back-Projecting Image Relationsn

Using the cropped chessboard images, we employ OpenCV's cv2.findChessboardCorners() function to automatically detect the pixel coordinates of the chessboard corners. Since the detected corner coordinates are based on the cropped images, we map these coordinates back to the global coordinate system of the original photo to accurately reflect their positions in the entire image. Subsequently, we use the chessboard corner coordinates from multiple photos, along with the chessboard's actual physical dimensions, to perform camera calibration. This process generates the intrinsic matrix and extrinsic matrix. The intrinsic matrix describes the camera's optical properties, such as focal length and principal point, while the extrinsic matrix determines the camera's spatial position and orientation. These parameters lay the foundation for subsequent image stitching tasks.


Figure 2: Camera Calibration

### 2.3 Stitching Images

1. **Method 1**: Use the extrinsic matrix to back-project how the images should be aligned and align the images relative to each other within a unified reference coordinate system. This method primarily relies on the camera's extrinsic parameters (e.g., position and orientation) to compute the relative transformations between images and achieve alignment.

2. **Method 2**: Use the four corners of the chessboard as reference points to calculate the transformation matrix, aligning all images to the same coordinate system. This method leverages clear geometric features for correspondence, enabling more accurate alignment, especially in scenarios with prominent features in the scene.

## 3 Result

Figure 3: Result From Method 1

From figure 3 we can see if we use the extrinsic matrix to directly back-project and rectify the photo, we get the poor result. We suspect that the poor performance is due to the different angles at which the two planes were captured, leading to a non-linear transformation. As a result, the solution can only serve as a linear approximation. When this error is applied to the entire image, it becomes more pronounced, resulting in greater distortion.

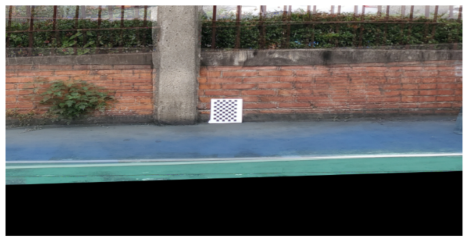

Figure 4: Result From Method 2

And from figure 4 we can observe if we use method. The image aligns well around the chessboard area. However, since the objects in the image are not originally on the same plane, the areas outside the chessboard become distorted due to trapezoidal correction, leading to additional errors.

# 4 Conclusion and Limitation

This time, we attempted to align images without using the traditional method of detecting feature points and applying RANSAC. Instead, we added special markers to the images and used them for alignment. This approach not only improves efficiency but also significantly reduces processing time when aligning multiple images, enhancing the overall speed and performance of the workflow.

Although the results of this experiment still need improvement, we observed that the errors are relatively smaller in areas near the reference points. If more reference points can be added to the scene, the outcomes are expected to improve significantly. Furthermore, in scenarios that require aligning a large number of images, this method can achieve more efficient image alignment.