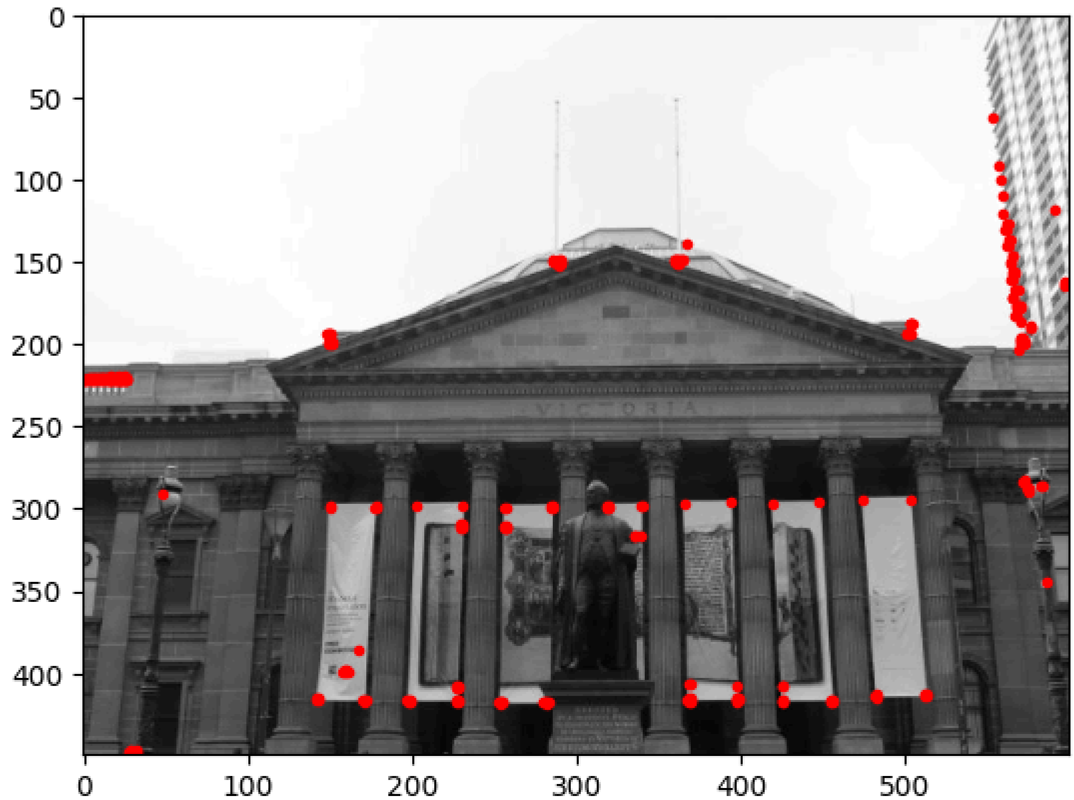
In this project I learned and used Adaptive Non-Maximal Suppression, Feature Descriptor, Feature Matching, Random Sampling Consensus and blending. The first step was to apply the Harris corner detection. After computing the corner response it is then passed in the Adaptive Non-Maximal Suppression (ANMS) algorithm as a parameter. The ANMS algorithm aims to identify and retain only the most significant corners while ensuring they are distributed evenly across the image. Initially, the algorithm identifies local maxima in the corner response map, representing potential strong corners. By computing the Euclidean distances between these local maxima, the algorithm evaluates their relative strengths and spatial distribution. The algorithm retains the top N strongest corners, as specified by the n_best parameter. This selective process ensures that redundant corners are discarded, leading to improved accuracy in tasks such as image stitching where the quality of corner selection directly influences alignment precision and overall visual coherence. The next step is the feature descriptors. Feature descriptors represent local image features that encode information about the surrounding area of a key point or interest point. These descriptors serve as a compact representation of the local image content, allowing for robust matching and recognition across different images. In this particular application, a patch size of 40x40 pixels centered around each key point is chosen. After obtaining the patches, Gaussian blur is applied to smooth the patch and reduce noise. The parameters of the Gaussian blur can be adjusted based on the specific application requirements. The resulting sub-sampled and blurred patch is then reshaped into a vector. To standardize this vector, each component is adjusted to have a zero mean and a variance of 1. After that is feature matching. Feature matching aims to establish correspondences between key points detected in two images, enabling the alignment and stitching of the images together. The goal is to find pairs of key points in the two images that represent the same underlying feature in the scene. The process of feature matching involves comparing the feature vectors of key points in one image with those in the other image. For each key point in the first image, distances are computed between its feature vector and all feature vectors in the second image. The best match is the point with the lowest distance, and the second-best match is also considered. By comparing the ratio of the distance of the best match to that of the second-best match, feature correspondences are retained if this ratio falls below a certain threshold.

Once the confident feature correspondences are identified, they are used to estimate the transformation (Homography) between the two images, which describes how one image should be warped or transformed to align with the other. Visualization of these corresponding features can be achieved using functions like drawMatches, which visually overlays the matched key points between the two images. The next step is Random Sampling Consensus (RANSAC), where in panoramic stitching is used to robustly compute the homography transformation between two images by iteratively selecting random subsets of feature correspondences, estimating the homography, and identifying inliers consistent with the transformation. By repeating this process and selecting the subset with the highest number of inliers, RANSAC effectively removes incorrect matches caused by noise or outliers. The final homography is then refined using the largest set of inliers, ensuring a more accurate alignment between images and enhancing the quality of panoramic stitching. Lastly warping and blending is done to combine the pairwise aligned images to generate the final panorama output. This step begins by warping each image according to the estimated homography matrix, ensuring that the transformed images align properly. The procedure outlined in the provided code involves calculating bounding boxes for each image after applying the homography and determining the largest bounding box that encompasses all transformed images. These bounding box dimensions serve as the canvas size for the panorama. Subsequently, a translation matrix is used to shift the upper-left corner of each image to (0,0), allowing all images to fit within the canvas. Finally, the common regions between overlapping images are blended together to create a seamless transition, ensuring that the stitched panorama accurately represents the scene. Various blending techniques can be employed, such as bilinear interpolation or taking the maximum or average of pixel values, to minimize visible artifacts and enhance the visual quality of the panorama.

In this project I referenced Ritik's feature descriptors and RANSAC algorithm's logic.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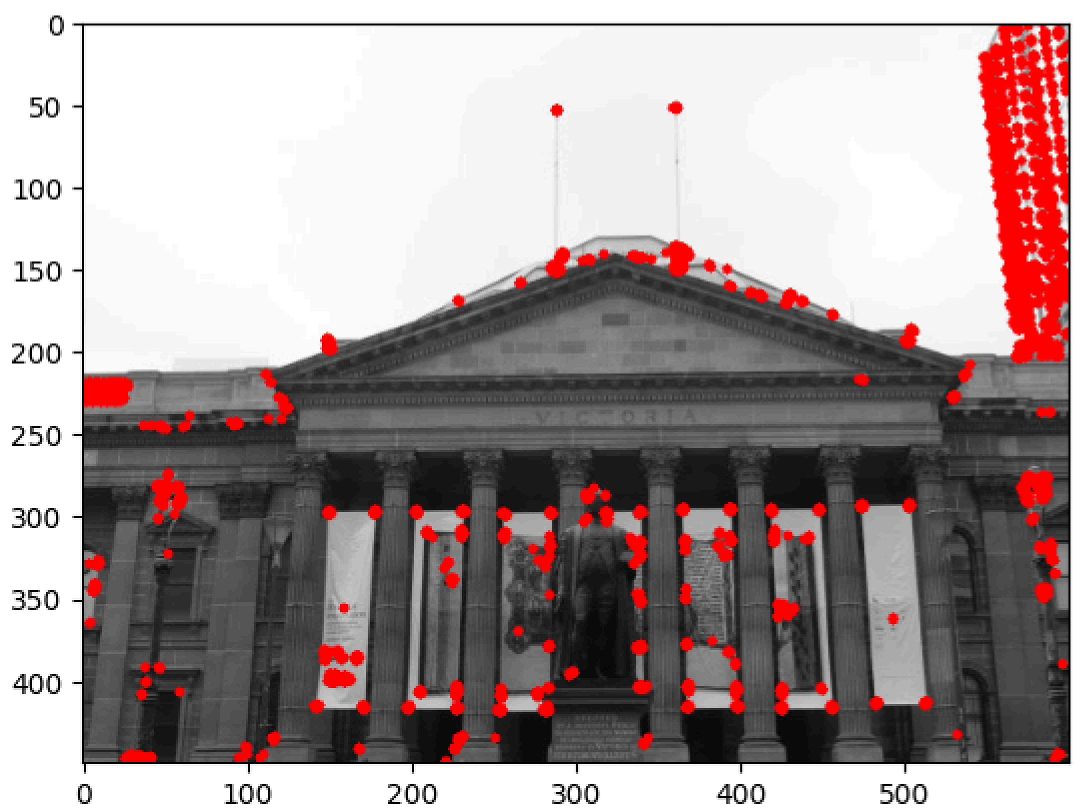
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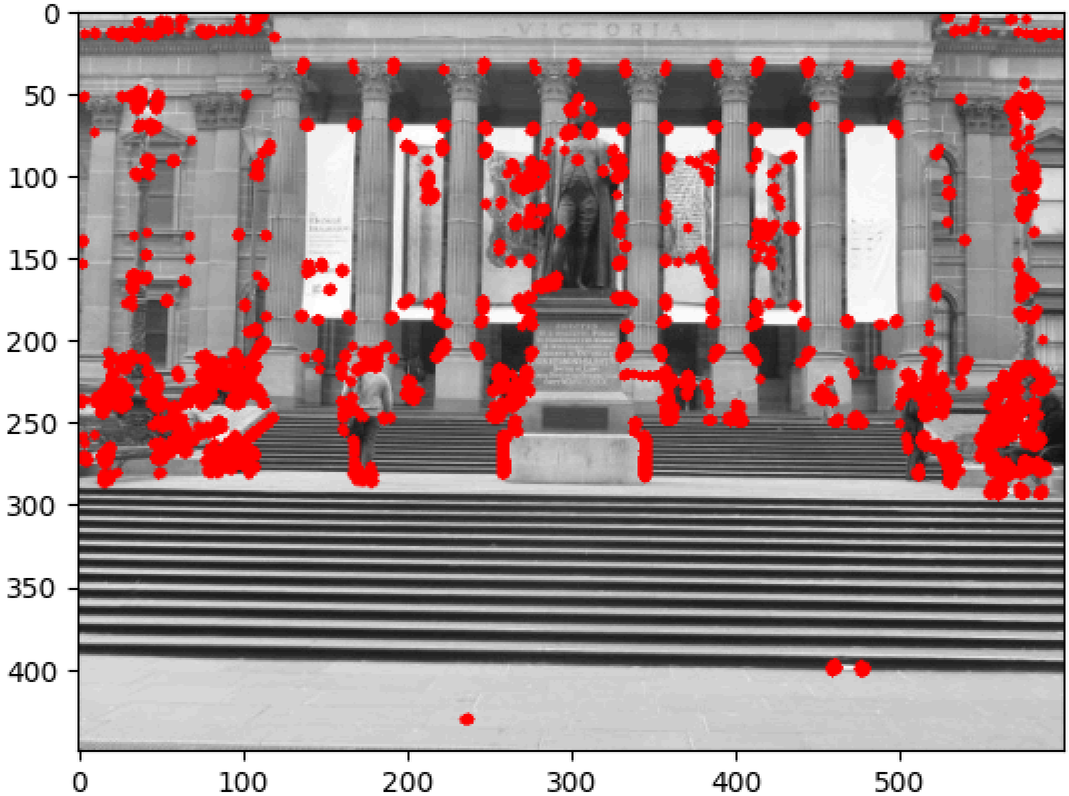
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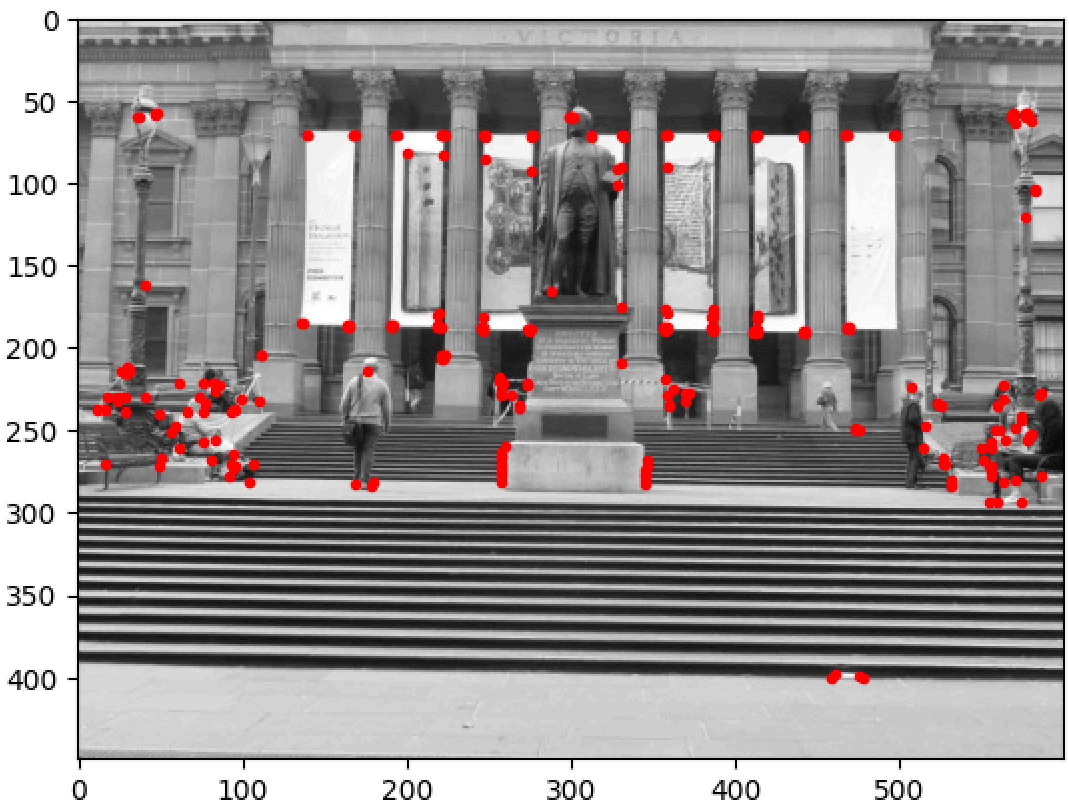
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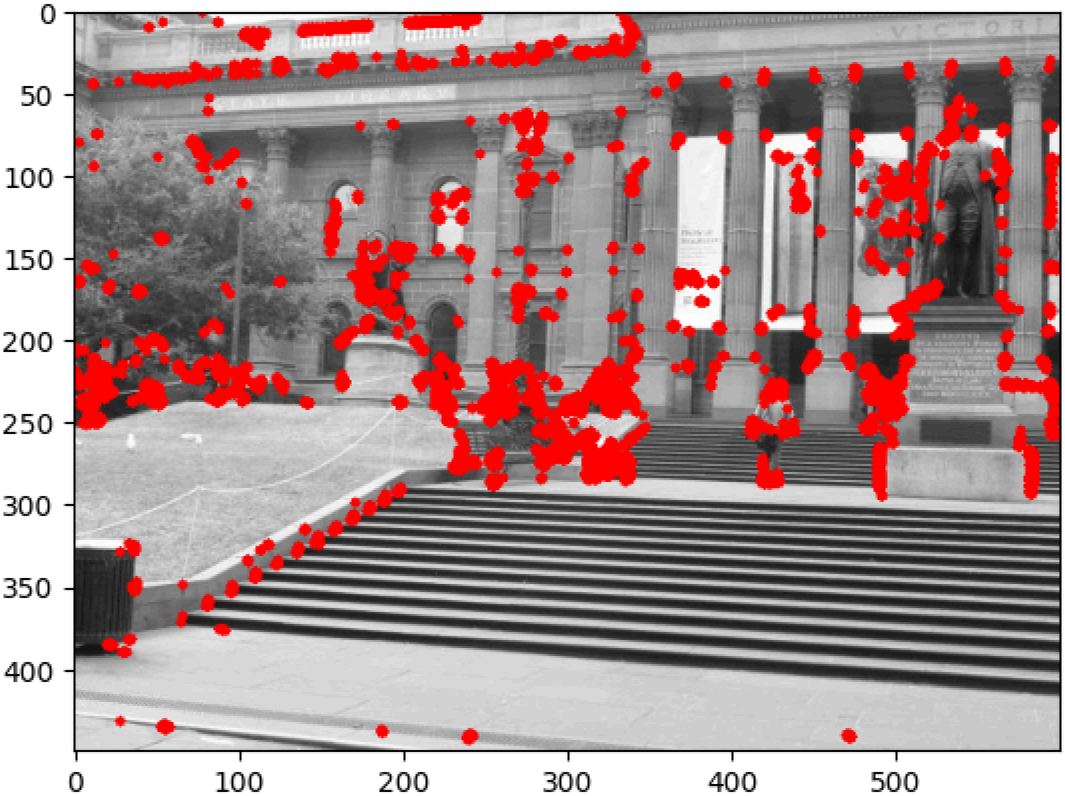
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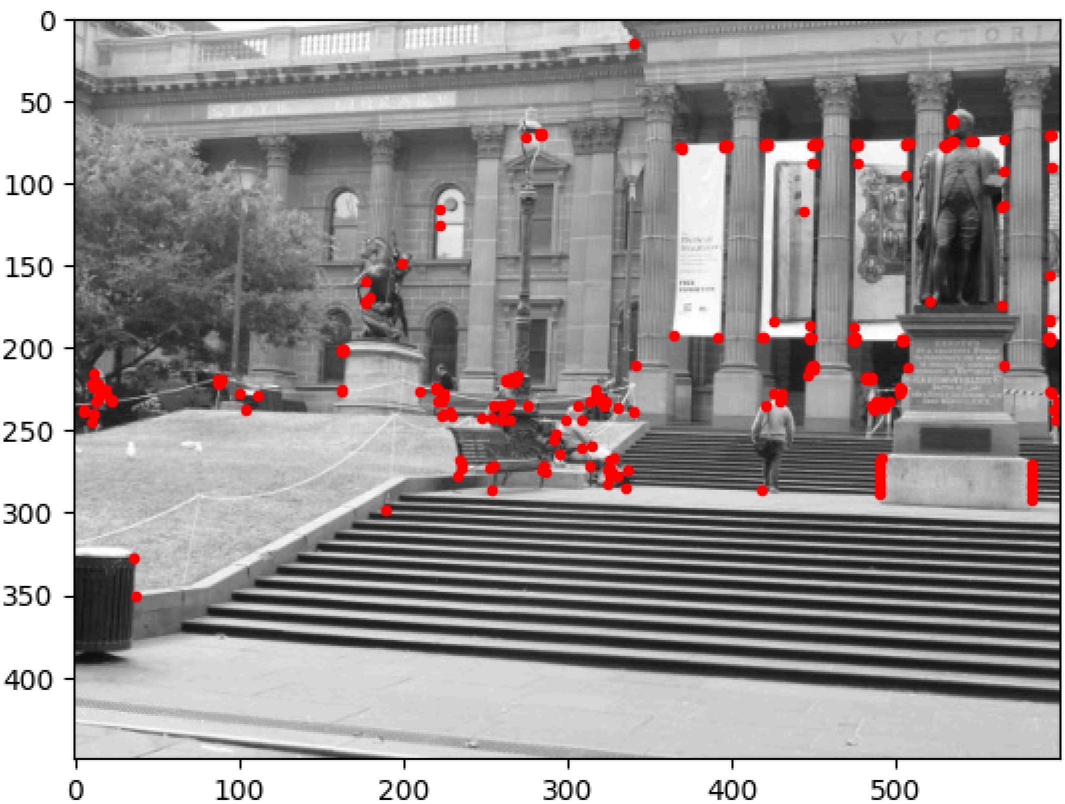
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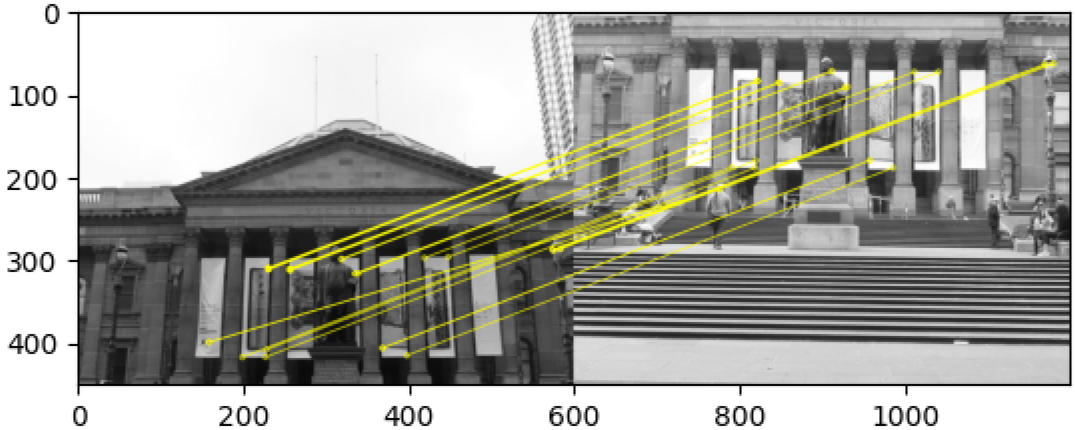
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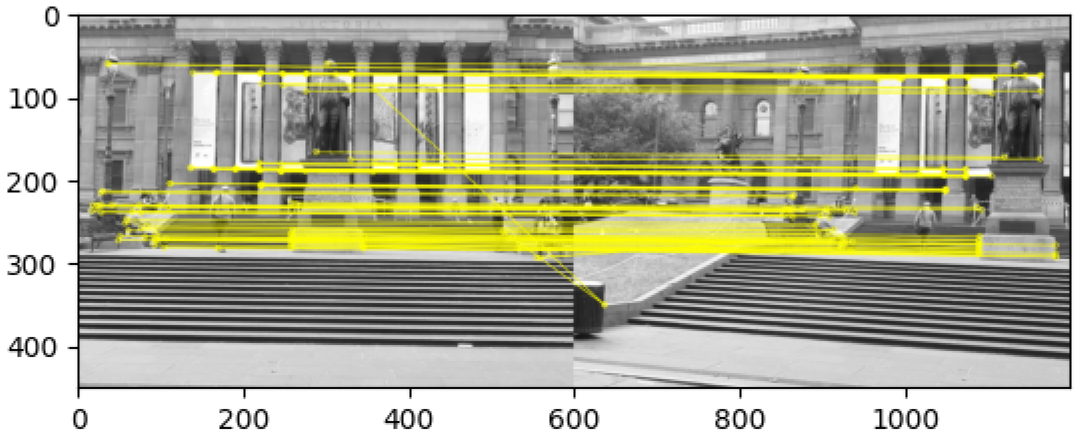
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