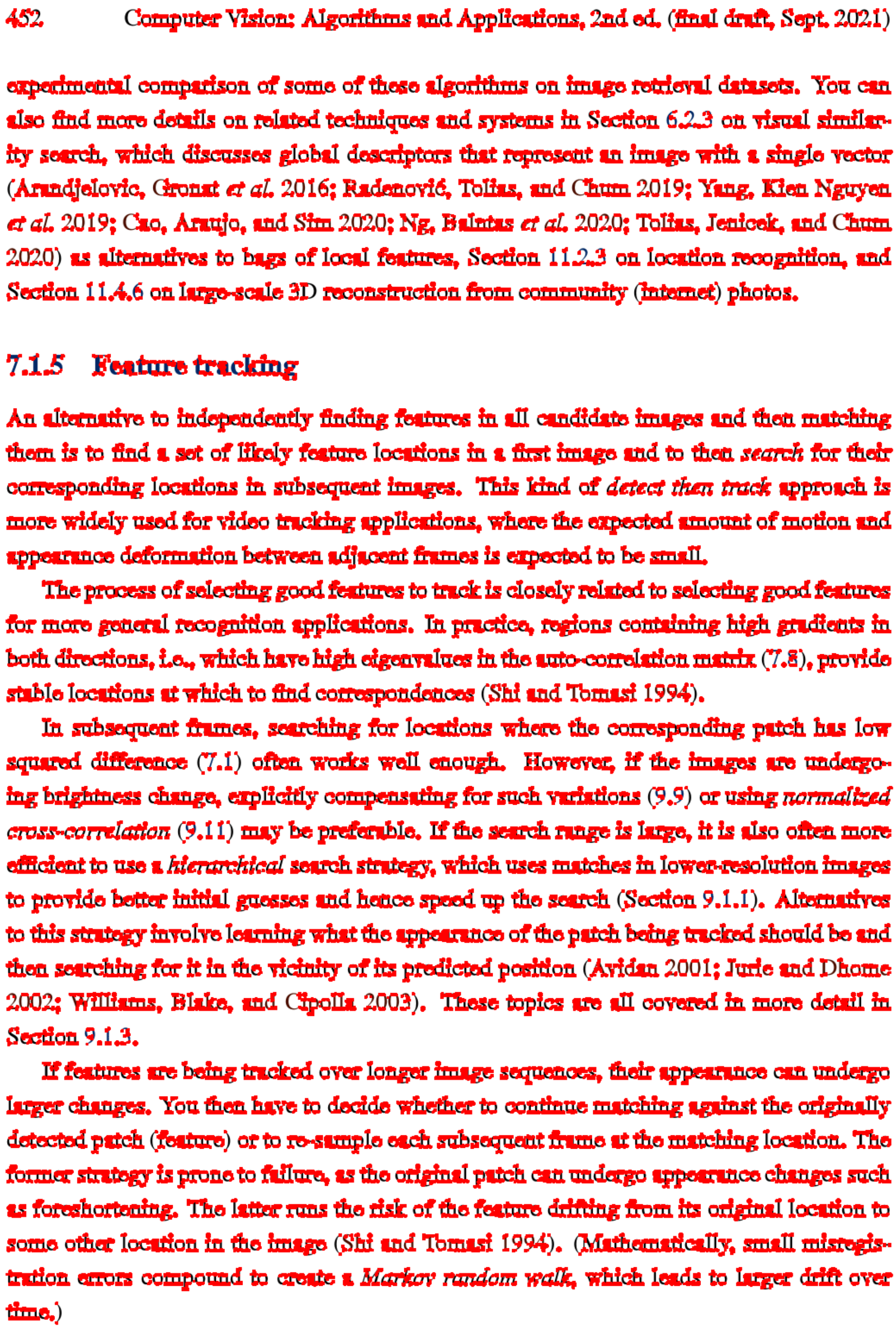
Harris Corner Detection (Page 1)

Harris Corner Detection was implemented using the function `harris_corner_detection(reference_image)`. It converts the image to grayscale, computes the Harris response, dilates it, and thresholds to mark corners in red.



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7.1.5 Feature tracking

An alternative to independently finding features in all candidate images and then matching them is to find a set of likely feature locations in a first image and to then *search* for their corresponding locations in subsequent images. This kind of *detect then track* approach is more widely used for video tracking applications, where the expected amount of motion and appearance deformation between adjacent frames is expected to be small.

The process of selecting good features to track is closely related to selecting good features for more general recognition applications. In practice, regions containing high gradients in both directions, i.e., which have high eigenvalues in the auto-correlation matrix (7.8), provide stable locations at which to find correspondences (Shi and Tomasi 1994).

In subsequent frames, searching for locations where the corresponding patch has low squared difference (7.1) often works well enough. However, if the images are undergoing brightness change, explicitly compensating for such variations (9.9) or using *normalized cross-correlation* (9.11) may be preferable. If the search range is large, it is also often more efficient to use a *hierarchical* search strategy, which uses matches in lower-resolution images to provide better initial guesses and hence speed up the search (Section 9.1.1). Alternatives to this strategy involve learning what the appearance of the patch being tracked should be and then searching for it in the vicinity of its predicted position (Avidan 2001; Jurie and Dhome 2002; Williams, Blake, and Cipolla 2003). These topics are all covered in more detail in Section 9.1.3.

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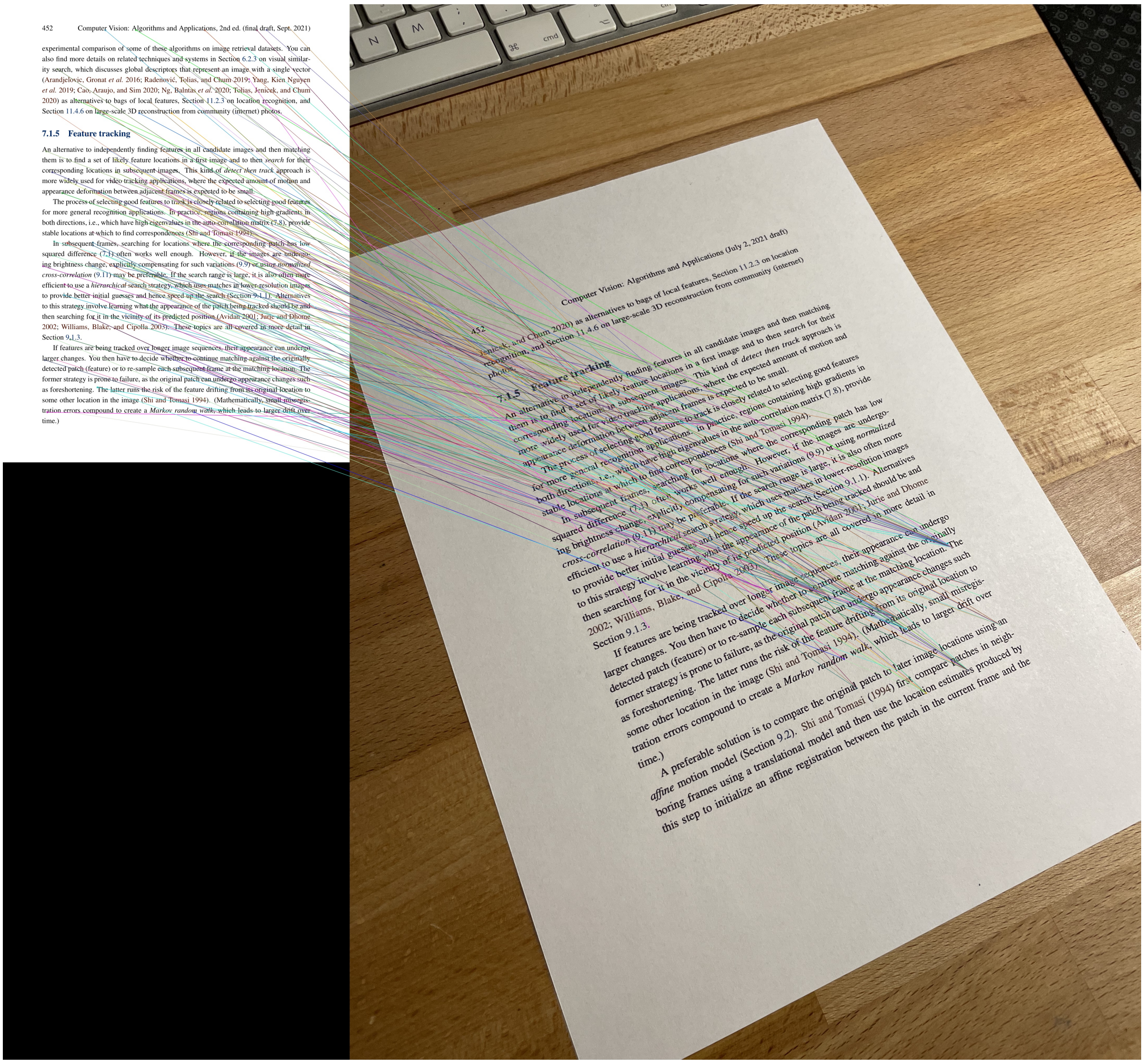
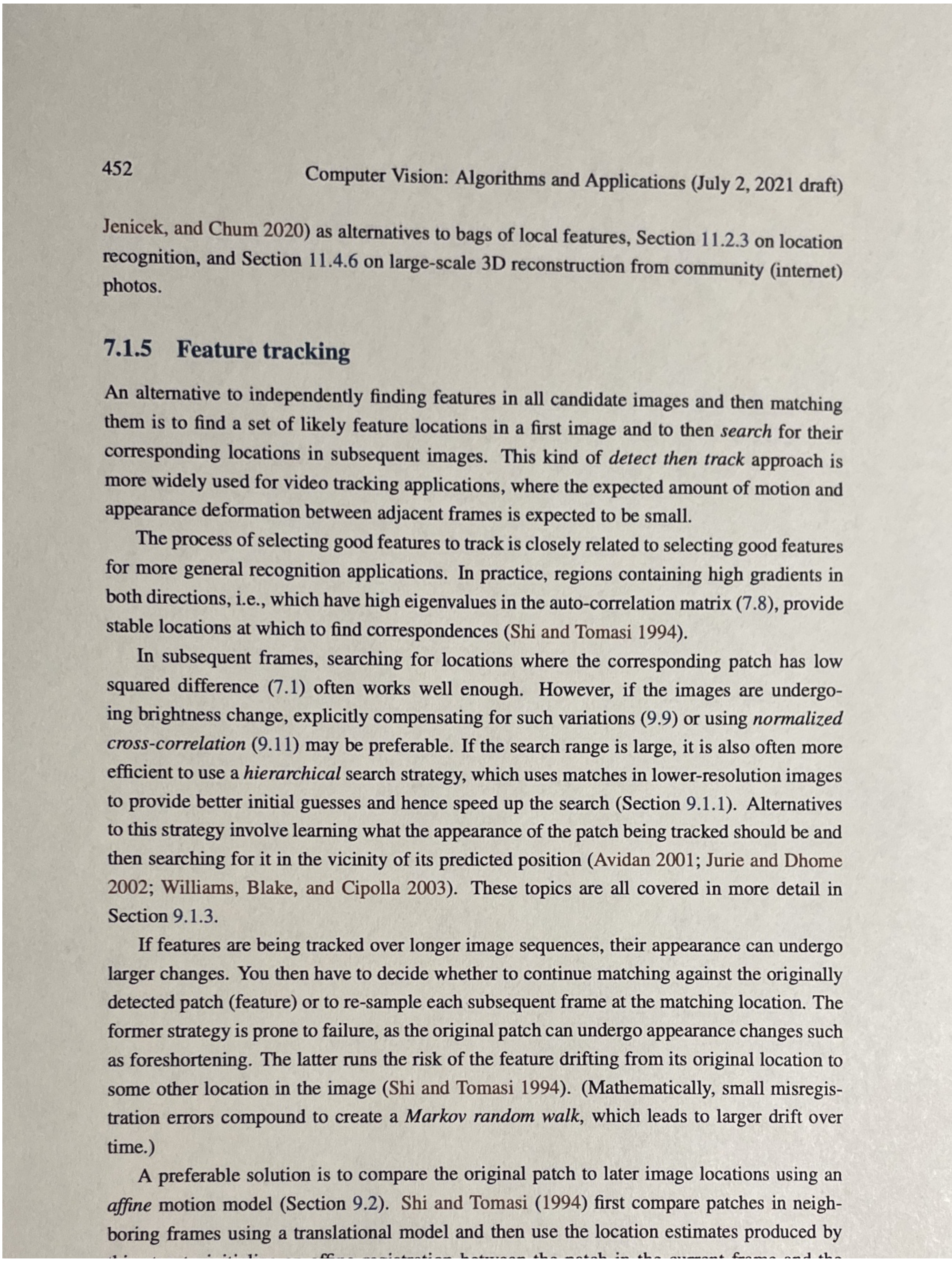
SIFT Feature Matches (Page 2)

SIFT detects robust keypoints that are invariant to scale, rotation, and illumination. Keypoints were matched between the reference and target image using a FLANN-based matcher. Lowe's ratio test was applied to select good matches. These matches were used as correspondence points for computing homography.



Aligned Image (Page 3)

After computing the homography using RANSAC, the second image was warped to align with the reference image.



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Conclusion

Harris Corner Detection provides a fast and effective way to detect stable keypoints. SIFT-based alignment extends this by detecting scale- and rotation-invariant features and using them for homography-based image alignment, producing a correctly aligned output image.

Harris Corner Detection and Feature-Based Image Alignment

Introduction

This assignment explores two computer vision techniques implemented in Python using OpenCV:

- Harris Corner Detection
- Feature-based Image Alignment using SIFT

The goal was to detect keypoints in a reference image and then align a second image using feature matches and homography. The reference image used was `reference_img.png`.

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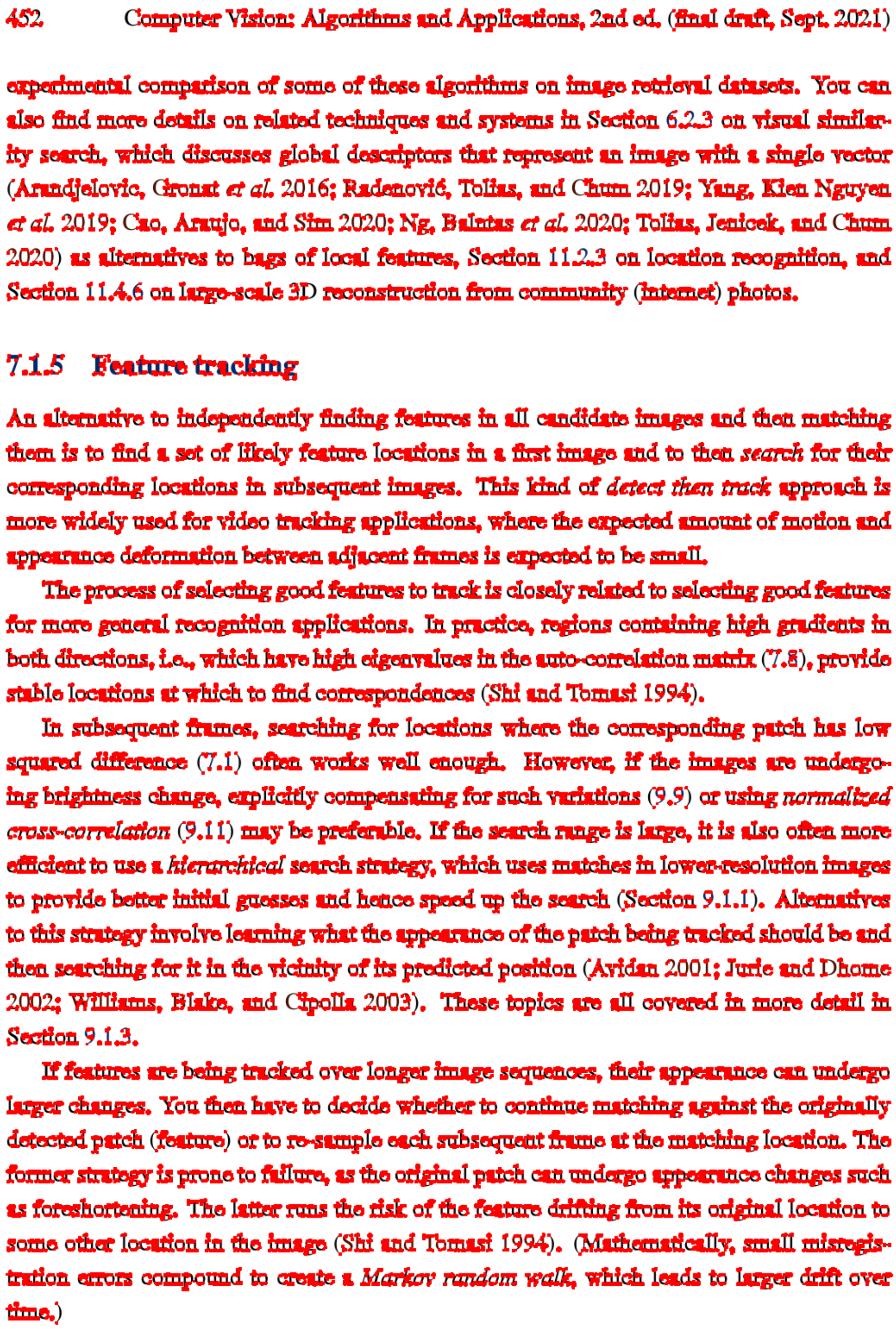

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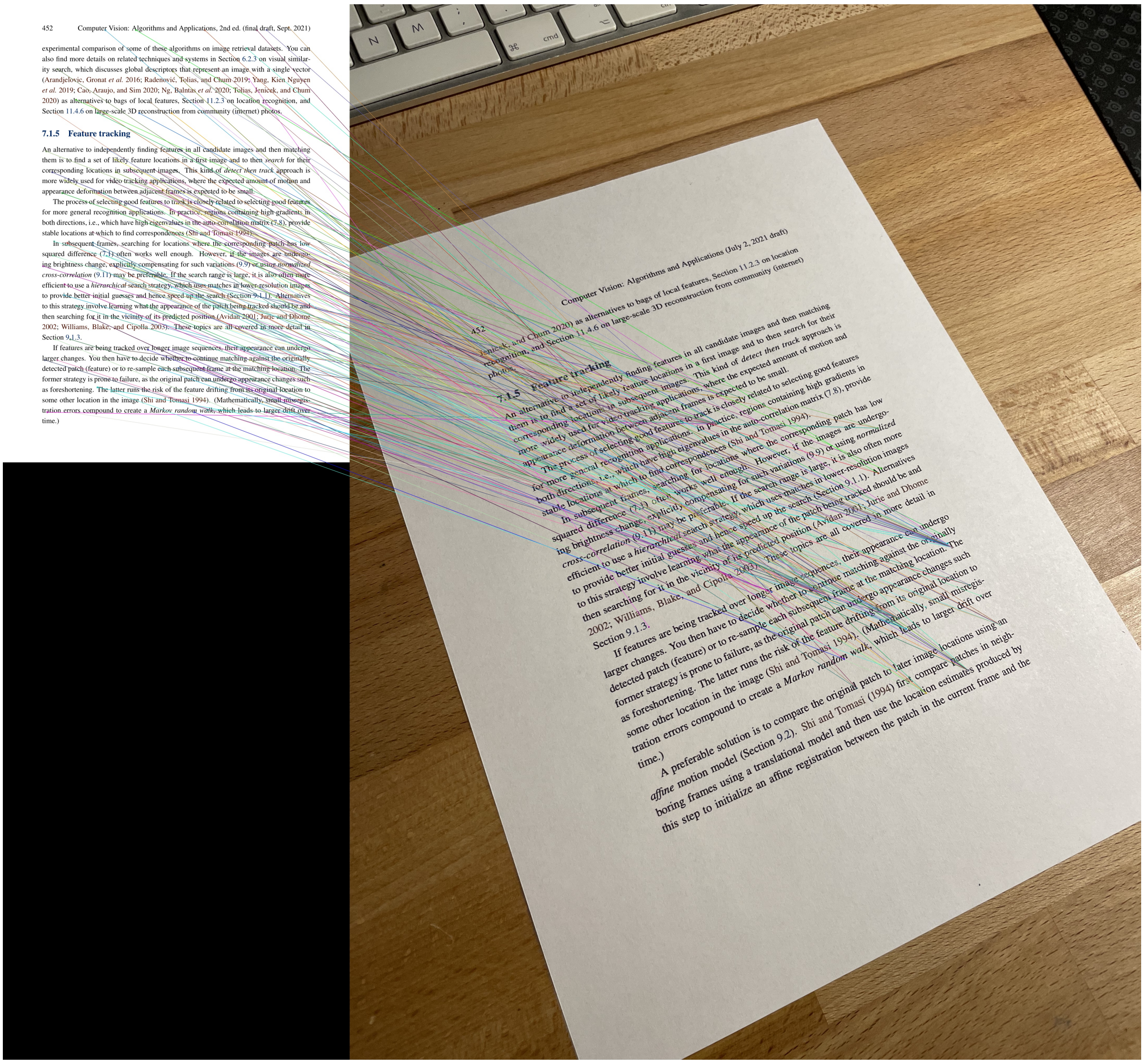

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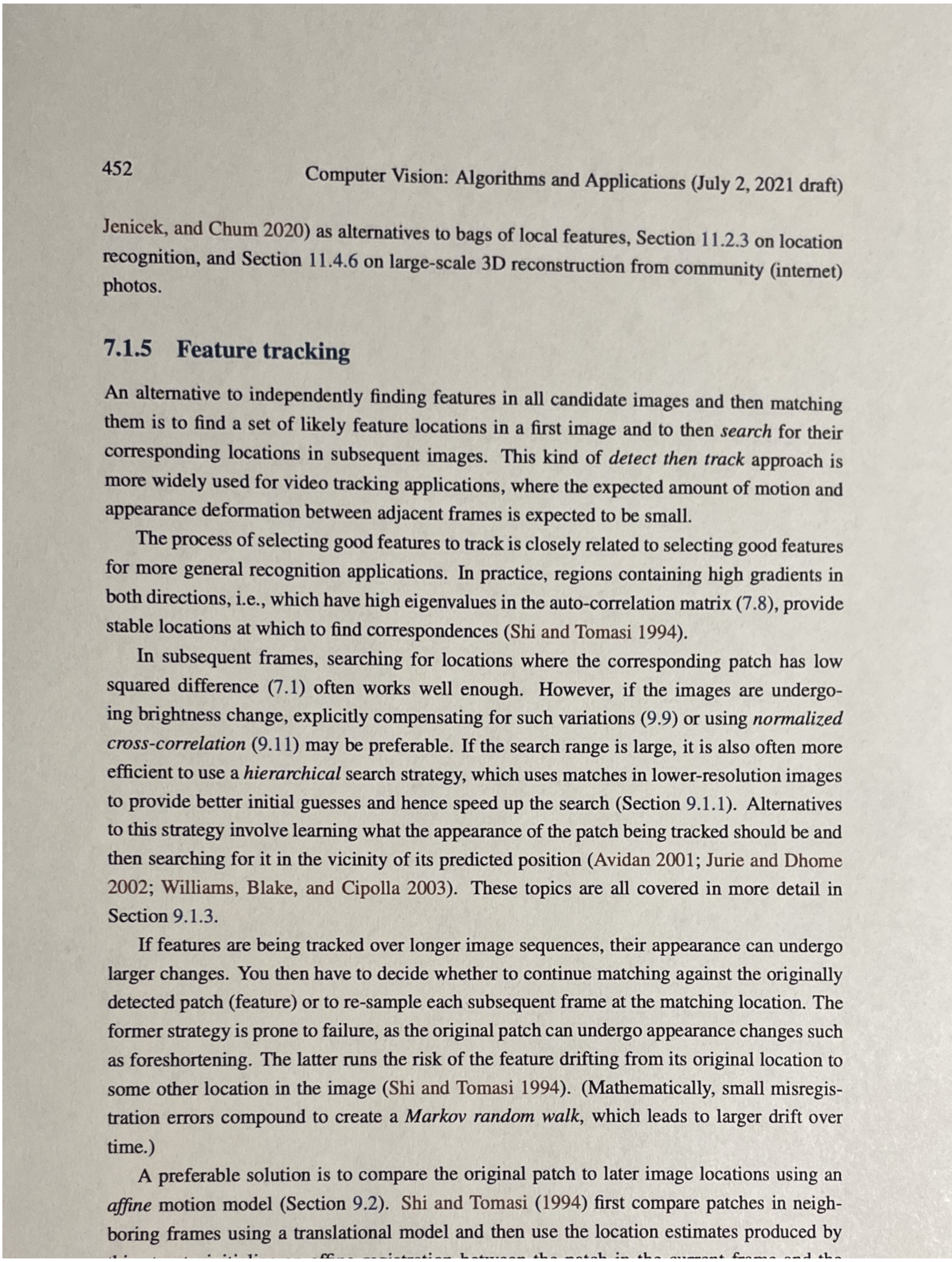

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