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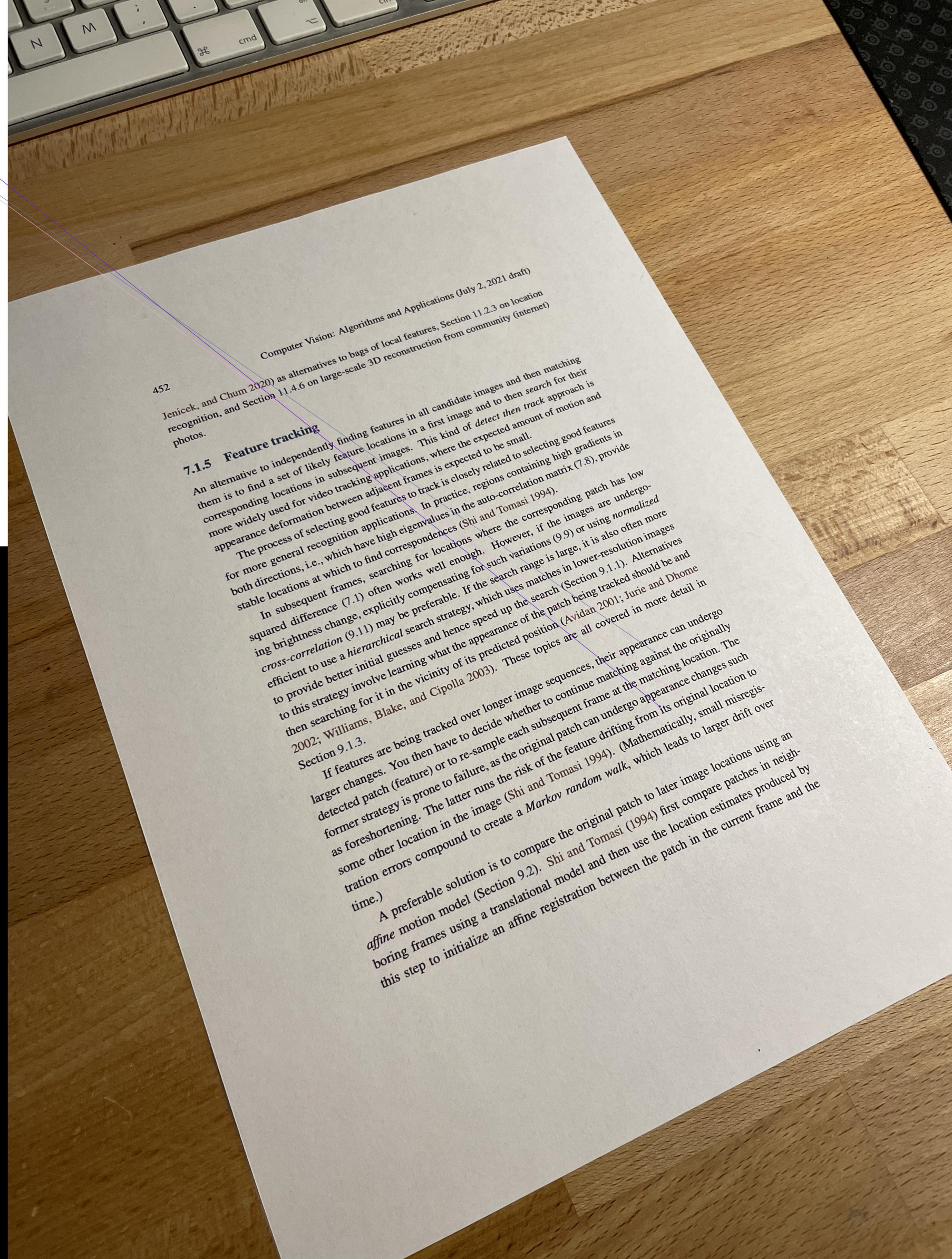

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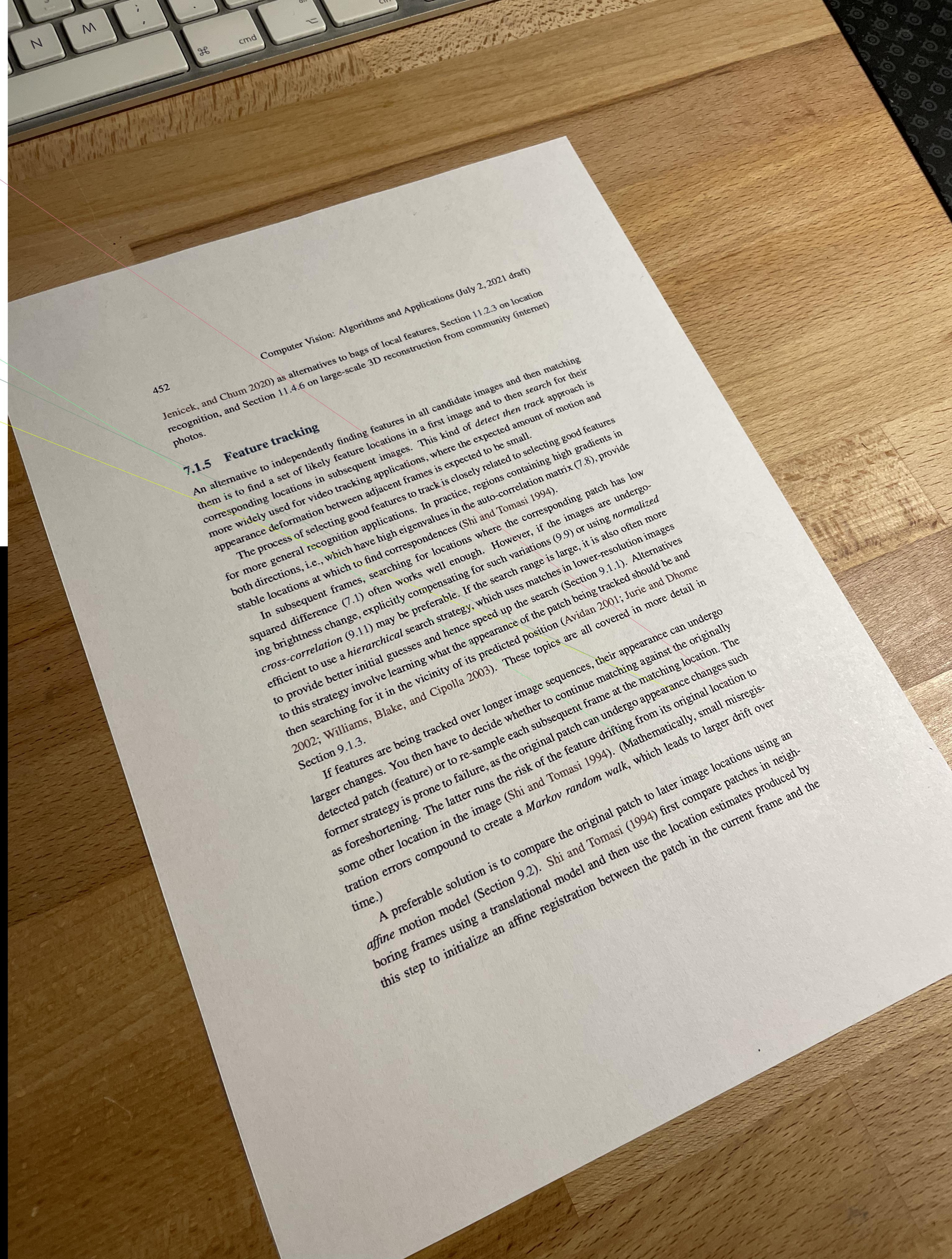

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A preferable solution is to compare the original patch to later image locations using an *affine* motion model (Section 9.2). Shi and Tomasi (1994) first compare patches in neighboring frames using a translational model and then use the location estimates produced by

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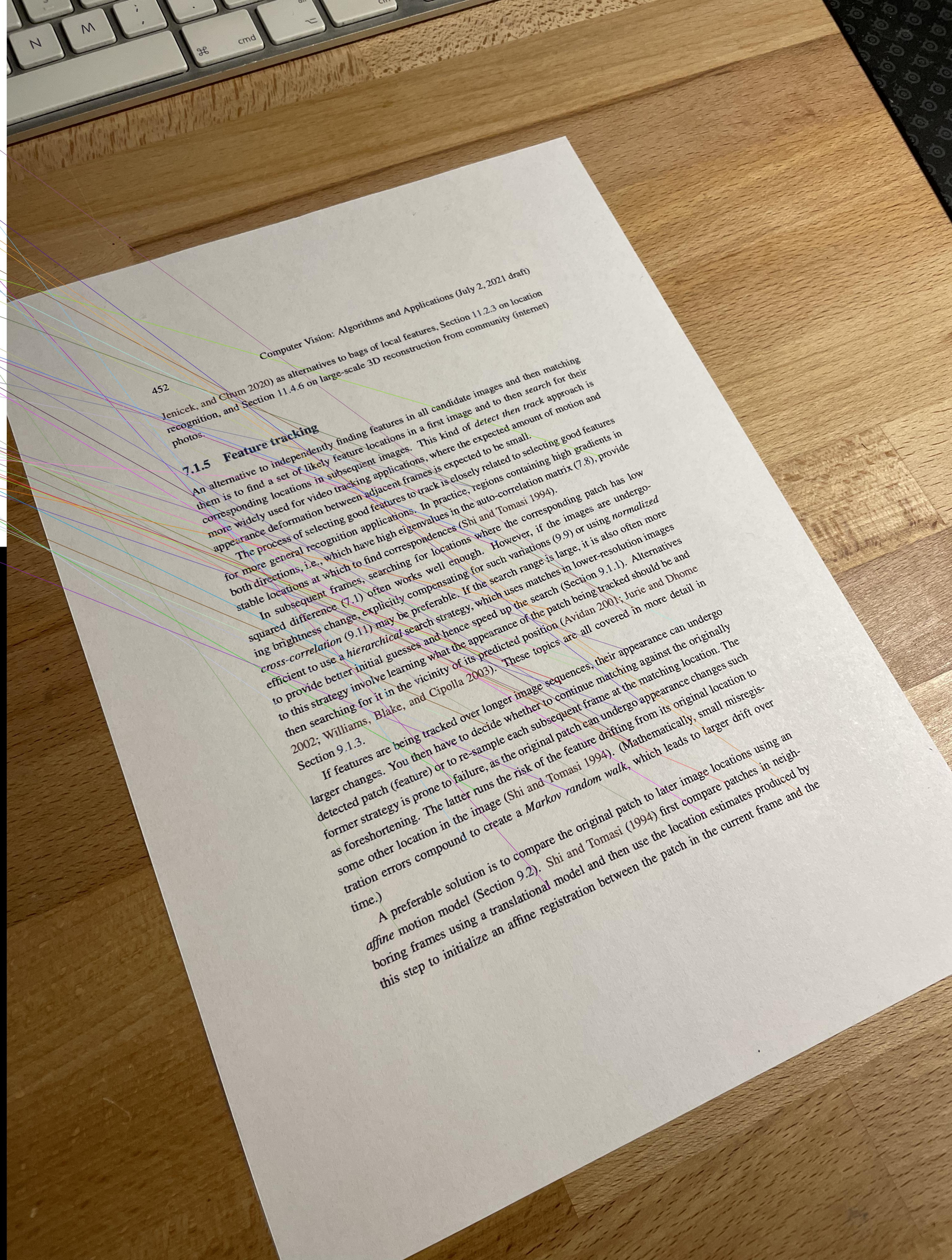
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