

Link to repository:

https://github.com/corneliusbrandt/IKT213_brandt/tree/main/assignment_4

Task 1

452 Computer Vision: Algorithms and Applications, 2nd ed. (final draft, Sept 2021)

experimental comparison of some of these algorithms on image retrieval datasets. You can also find more details on related techniques and systems in Section 6.2.3 on visual similarity search, which discusses global descriptors that represent an image with a single vector (Arandjelovic, Gronat *et al.* 2016; Radenović, Tolias, and Chum 2019; Yang, Kien Nguyen *et al.* 2019; Cao, Araujo, and Sim 2020; Ng, Balntas *et al.* 2020; Tolias, Jenicek, and Chum 2020) as alternatives to bags of local features, Section 11.2.3 on location recognition, and Section 11.4.6 on large-scale 3D reconstruction from community (internet) photos.

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 Dhume 2002; Williams, Blake, and Cipolla 2003). These topics are all covered in more detail in Section 9.1.3.

If features are being tracked over longer image sequences, their appearance can undergo larger changes. You then have to decide whether to continue matching against the originally detected patch (feature) or to re-sample each subsequent frame at the matching location. The former strategy is prone to failure, as the original patch can undergo appearance changes such as foreshortening. The latter runs the risk of the feature drifting from its original location to some other location in the image (Shi and Tomasi 1994). (Mathematically, small misregistration errors compound to create a *Markov random walk*, which leads to larger drift over time.)

Task 2

Used Method: SIFT

Jenicek, and Chum 2020) as alternatives to bags of local features, Section 11.2.3 on location recognition, and Section 11.4.6 on large-scale 3D reconstruction from community (internet) photos.

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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.

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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

experimental comparison of some of these algorithms on image retrieval datasets. You can also find more details on related techniques and systems in Section 6.2.3 on visual similarity search, which discusses global descriptors that represent an image with a single vector (Arandjelovic *et al.* 2016; Radenović, Tolias, and Chum 2019; Yang, Kien Nguyen *et al.* 2019; Cao, Araújo, and Sim 2020; Ng, Balntas *et al.* 2020; Tolias, Jenícek, and Chum 2020) as alternatives to bags of local features. Section 11.2.3 on location recognition, and Section 11.4.6 on large-scale 3D reconstruction from community (internet) photos.

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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 (C_{AB}), provide stable locations at which to find correspondences (Shan and Gehler, 1994).

In subsequent frames, searching for features where the corresponding pixels have been squared difference (11) often work well enough. If this is the case, then the algorithm can ignore brightness changes explicitly compensating for such variations, as was done in our original cross-correlation (19). It may be preferable if the search range is large, as it is more efficient to use a hierarchical search strategy which divides the search area into smaller regions to provide better initial matches and hence reduce the search time. In this paper we decided to provide only one learning rule and the appearance of the patch based on (11) should be used for this searching for the initial assembly of the predicted patch (see section 3.1.1, 2002; Williams, Blake, and Crowley 1999). These types of rules have proved to be more effective than the ones proposed by Williams et al. (2002).

If features are being tracked over longer time steps, then appearance can change significantly. You then have to decide whether to continue matching against the originally detected feature (feature A) or sample each subsequent frame in the hope of finding a new feature strong enough to replace it. An incremental policy is under development, such as for *Surveillance*. The idea is that if the feature drifts too far, it will be moved to some other location in the image (see [Fig. 9.16](#) and [Table 9.1](#)). A mathematically rigorous re-orientation error compound to create a *Mitsubishi* effect, which leads to increased tracking time.)

Matches