Abstract

Finding reliable correspondences between sets of feature points in two images remains challenging in the presence of ambiguity or strong transformations. We introduce a 2nd-order photometric descriptor for virtual lines joining two neighbouring feature points.

Intuition

Our approach is based on the fact that, for any two points \( P_i, P_j \) in image \( I_1 \), and any two points \( P'_i, P'_j \) in image \( I_2 \), it is unlikely to find similar photometric information around lines \( (P_i, P'_j) \) and \( (P'_i, P_j) \) unless both \( (P_i, P'_j) \) and \( (P'_i, P_j) \) are correct matches.

Virtual Line Descriptor (VLD)

The virtual line for \( P_i \) and \( P_j \) in image \( I_1 \) is covered by \( U \) disks \( D_k \) of radius \( r = \frac{d}{t+1} \). Each disk is described by a SIFT-like descriptor. The global, virtual line descriptor is the concatenation of all disk descriptors.

K-VLD matching method

We introduce a novel semi-local 2nd-order matching method. It considers both geometric and photometric consistency. The basic idea of K-VLD relies on the fact that, given a potential match \( (P_i, P'_j) \), if there are at least \( K \) other matches \( (P_k, P'_j) \) \( k \in \{1, \ldots, K\} \) that are K-VLD-consistent (for geometrical consistency) with \( (P_i, P'_j) \), then the \( (P_i, P'_j) \) is likely to be a correct match. The K-VLD algorithm starts with all the potential matches and iteratively removes matches that have less than \( K \) K-VLD-consistent neighbors and matches that do not satisfy the extra geometric constraint, until no match is removed.

Filtering matches

We show the capacity of K-VLD in filtering matches. First we test a pair of synthetic images where nearest neighbour and geometric information are not sufficient [1] (Fig 1, 2). Second we test K-VLD as a pre-filter to RANSAC-based calibration (ORSA) [4] using Strecha’s castle dataset [2]. Fig 3 visually illustrates improvement by K-VLD, and angle errors are measured after one round (Fig 4).

Fig 1. SIFT (Low score=0.499, no symmetry) then filtered by K-VLD.

Fig 2. ASIFT (Low score=0.73 no symmetry) then filtered by K-VLD.

Fig 3. The castle dataset. Left: inliers by ORSA. Middle: false matches near epipolar lines by ORSA rejected by K-VLD. Right: inliers by K-VLD + ORSA.

Fig 4. Angle error on the castle dataset. Left: average error over 19 image pairs. Right: accumulated error after one loop.

Comparison with graph matchers

We experimented with various matching methods: probabilistic hypergraph matching (HGM), tensor matching, hypergraph matching via rewritten random walks, spectral matching (SM) / integer projected fied point, and game-theoretic matching. We also augmented methods SM and HGM with our VLD, and we compared with K-VLD. We evaluated matching accuracy worst-case changing imaging conditions with Mikolajczyk’s dataset. We also evaluated the case of strong occlusion with Détienne fountain’s dataset (Fig 5).

Fig 5. Détienne fountain: K-VLD clusters & average accuracy.

Reference

[4] Monko, P.; Monko, P; Morisse, B. Automatic homomorphic registration of a pair of images, with a centrodiagonalm oleation of outliers. In IPOL 2012