Robust Image Matching with Line Context

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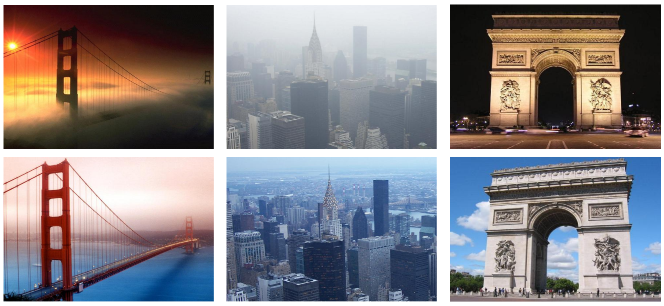


(a) (b) (c)

Figure 1: The challenging cases for image matching in different illuminating environments. The photos on top are taken in (a) the sunlight (b) a rainy day (c) night time. The photos at bottom are taken in a normal daytime.

Some features are specially designed to cope with complex illumination variations [1, 2, 3, 4, 5]. These features are based on intensity orders rather than values so that their descriptors are invariant to non-linear intensity changes. However, one limitation of such features is that they are only able to handle monotonic illumination changes, as the examples shown in Figure 1. In this paper, we try to cope with this problem by proposing a new type of local feature, which describes the context information of neighboring line segments.

Through extensive experiments and based on existing research, we found that the best pixel grouping level to handle large illumination variations is using curves or lines. Since curves require more sophisticated groupings and can be approximated by multiple line segments, we use line segments as the primitives of our feature descriptor. We call the proposed feature *Line Context*, since it is inspired by *Shape Context*.

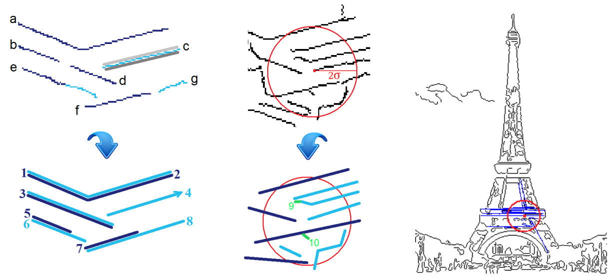
Line Context Detector. It is well known that edges are present at various scales. To detect edges at different scales we use multi-scale Canny edge detector with Gaussian derivatives at several pre-selected scales. Two phases are used to remove unstable edges. The first phase is to apply Laplacian operator. Those edges that do not attain a distinctive extremum over scales will be removed. The second phase is to remove those edges with homogeneous gradients, i.e. the points where the underlying curves have zero curvatures. We apply Harris matrix to achieve this purpose.

Segments in Context. The edge pixels are linked to connected curves at different scales. These curves are then fitted by straight line segments. As shown in Figure 2-(a), several cases need to be considered for representing curves with line segments. One curve may be fitted by multiple segments like *curve a*. Two segments with small gap in between are merged into one larger segment no matter they are on the same scale (*curve b* and *d*) or different scales (*curve f* and *g*). In the latter case, the merged segment only exists in the lower scale (*segment* 8). Besides, all the segments in higher levels are also segments (*segment* 1, 2 and 3) or part of segments (*segment* 5 and 7) in lower levels.

For each keypoint, we need to find line segments in its neighborhood, which is also called *context* of the feature. The line segments lying inside or partially inside the context are called *context segments*. The initial scale σ provides an estimate size of searching area. Let $d_{point-set}(v,S)$ be the shortest distance from point v to a set of points S. With keypoint k and all-segments $\{seg_i\}$, the segments set L in the context is defined as,

$$L(k) = \{seg_i | d_{point-set}(k, seg_i) \leq 2\sigma\} \tag{1}$$

Figure 2-(b) shows an example of context segments. All the segments in scale level σ and *lower* scales are included in the context as long as part of the segment is within distance 2σ. Note that segments with very small lengths are removed because these segments are unstable on different images (*segment* 9 and 10). The feature descriptor will be formed by the remaining segments. Figure 2-(c) shows a keypoint and its context segments on an image after edge detection.



(a) (b) (c)

Figure 2: (a) Curves at various scales are fitted by line segments in different situations. Dark blue denotes higher scale level, and light blue denotes lower scale level. (b) Line segments within distance 2σ are considered context segments. (c) A keypoint and its context segments on an edge image.

Scale and Orientation. The *Line Context* feature is designed to be scale and rotation invariant. Let m_i be the midpoint of segment seg_i in the context of keypoint k, $d_{point-point}(a,b)$ be distance between two points a and b. The scale s for the feature is defined as,

$$s(k) = \frac{\sum_{seg_i \in L(k)} d_{point-point}(k, m_i)}{|L(k)|} \tag{2}$$

During descriptor calculation process, all the context segments of keypoint k will be normalized by a factor of $s(k)$.

Each keypoint descriptor is assigned a canonical orientation so that the descriptor is invariant to rotations. This orientation is determined by the dominant orientation of *context segments* in the *lowest* edge scale.

Line Context Descriptor. We use multiple sampled points as the representation of segments in the context. Four parameters are used to describe each sample point. They are 1) the distance r to the keypoint, 2) the angle $\alpha \in [0,360)$ between the direction from keypoint to sample point and reference direction (keypoint dominant orientation), 3) the angle $\beta \in [-180,180)$ between reference direction and the orientation of underlying segment and 4) the underlying segment scale σ. After sampling, all the sample points will be used to form the keypoint descriptor.

Our goal is to produce a compact descriptor for each keypoint by computing a coarse histogram of the relative coordinates of segment sample points. We use a log-polar-like coordinate system to vote for the relative distances. The accumulated weights from all sample points form a 3D descriptor. Many bins have 0 vote which are similar to SIFT descriptors. Through experiments, we found that it is usually not necessary to cover segments in all scales. The scale σ_0 and one level lower are good estimations for most cases.

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