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Uniform competency-based local feature extraction for remote sensing images

Amin Sedaghat *, Nazila Mohammadi

Department of Geomatics Engineering, Faculty of Civil Engineering, University of Tabriz, Tabriz, Iran

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ABSTRACT

Local feature detectors are widely used in many photogrammetry and remote sensing applications. The quantity and distribution of the local features play a critical role in the quality of the image matching process, particularly for multi-sensor high resolution remote sensing image registration. However, conventional local feature detectors cannot extract desirable matched features either in terms of the number of correct matches or the spatial and scale distribution in multi-sensor remote sensing images. To address this problem, this paper proposes a novel method for uniform and robust local feature extraction for remote sensing images, which is based on a novel competency criterion and scale and location distribution constraints. The proposed method, called uniform competency (UC) local feature extraction, can be easily applied to any local feature detector for various kinds of applications. The proposed competency criterion is based on a weighted ranking process using three quality measures, including robustness, spatial saliency and scale parameters, which is performed in a multi-layer gridding schema. For evaluation, five state-of-the-art local feature detector approaches, namely, scale-invariant feature transform (SIFT), speeded up robust features (SURF), scale-invariant feature operator (SFOP), maximally stable extremal region (MSER) and hessian-affine, are used. The proposed UC-based feature extraction algorithms were successfully applied to match various synthetic and real satellite image pairs, and the results demonstrate its capability to increase matching performance and to improve the spatial distribution. The code to carry out the UC feature extraction is available from https://www.researchgate.net/publication/317956777_UC-Feature_Extraction.

1. Introduction

Local feature-based image matching plays a critical role in many photogrammetry, remote sensing and computer vision tasks, such as image registration (Gerçek et al., 2016; Tsai and Lin, 2017; Zhao and Goshtasby, 2016), change detection (Fytsilis et al., 2016; Huang et al., 2017), image fusion (Klonner et al., 2015; Teimouri et al., 2016) and 3D reconstruction and modelling (Eltner and Schneider, 2015; Konugurthi et al., 2016).

A local feature can be defined as an image pattern or distinct structure with properties differing from its immediate neighbourhood. The most important property of a local feature is robustness, which can be defined as feature's stability against a variety of image geometric and photometric transformations. Beyond feature robustness, most local feature detector algorithms extract three types of features (Fig. 1):

(1) Rotation-invariant features: Rotation-invariant features, which have also been referred to as points and corners, correspond to points in the 2D image with high curvature or strong two-dimensional intensity changes. The most popular point feature detector algorithms are Harris (Harris and Stephens, 1988), Hessian (Beaudet, 1978), phase congruency (Kovesi, 2003) and FAST (Rosten et al., 2010). Point features are naturally invariant to translation and rotation, as well as robust to illumination changes and limited changes of viewpoint. On the other hand, they are sensitive to scale and significant viewpoint differences, and they do not provide a good basis for multi-sensor image matching.
(2) Scale-invariant features: To deal with scale changes, scale-invariant approaches have been introduced which automatically determine both the location and scale of the local features using scale-space theory (Lindeberg, 2008). These

* Corresponding author.
E-mail addresses: am.sedaghat@gmail.com (A. Sedaghat), n.mohammadi@tabrizu.ac.ir (N. Mohammadi).

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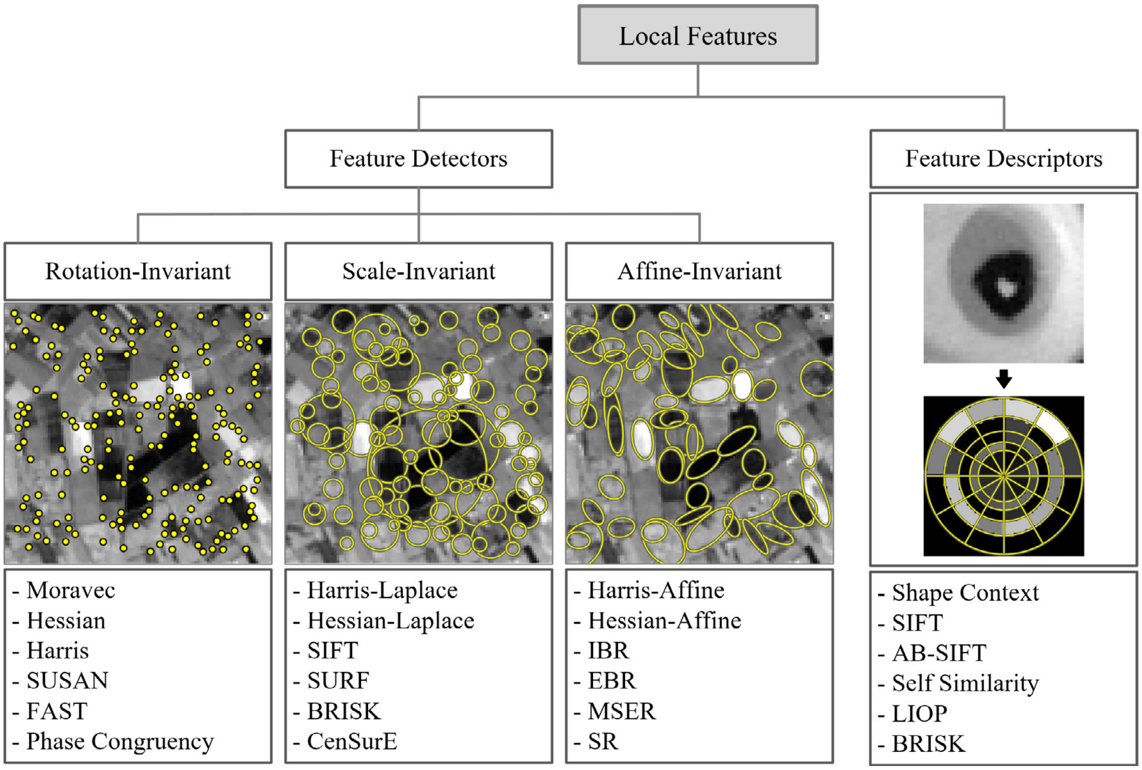

Fig. 1. Local feature algorithms.

features are typically circular regions. The majority of scale-invariant detectors are based on the Gaussian second derivative filter (Mainali et al., 2013). The automatic scale selection based on the scale-normalized Laplacian of Gaussian (Lindeberg, 1998), scale-invariant feature transform (SFIT) (Lowe, 2004), Harris-Hessian Laplace (Mikolajczyk and Schmid, 2004), speeded-up robust features (SURF) (Bay et al., 2008), scale-invariant feature operator (SFOP) (Forstner et al., 2009), and binary robust invariant scalable keypoints (BRISK) (Leutenegger et al., 2011) algorithms are the most prominent scale-invariant feature detectors.

(3) Affine-invariant features: The uniform scaling in scale-invariant detectors cannot effectively deal with significant viewpoint differences. For viewpoint changes, the most interesting transformation is an affinity (Mikolajczyk et al., 2005). To achieve reliable matching over a wider viewpoint angle, the affine-invariant approaches have been introduced. The output shape of most affine-invariant algorithms, such as Harris/Hessian-Affine (Mikolajczyk and Schmid, 2004), the intensity extremal-based region detector (IBR) (Tuytelaars and Van Gool, 2004), and the salient region detector (Kadir et al., 2004) are originally elliptical regions. However, for simplicity, the other types of extracted features are also replaced by an ellipse. Examples of this are irregular maximally stable extremal regions (MSER) (Matas et al., 2004) and the parallelogram-shaped features of the edge-based region (EBR) detector (Tuytelaars and Van Gool, 2004).

Since scale- and affine-invariant features generally need to characteristic scale selection and affine shape estimation process, their computation complexity is relatively higher than that of point feature detector algorithms. Local feature are usually associated with descriptors to characterize and match them. A feature descriptor is generally a numerical vector that encodes the properties of the local feature image neighbourhood. Many different descriptors have been developed in the literature (Fan et al., 2016; Lee and Park, 2017). SIFT (Lowe, 2004), DAISY (Tola et al., 2010), LIOP (Wang et al., 2011), and BRISK (Leutenegger et al., 2011) are a few notable examples of local feature descriptors. After local feature detection and description from two images, the correspondence process is established using a particular similarity measure such as the Euclidean or Mahalanobis distance.

Local features have received a lot of attention in the photogrammetry and remote sensing community (Castillo-Carrión and Guerrero-Ginel, 2017; Duan et al., 2016; Kehl et al., 2017). In the last decades, a large number of remote sensing image matching and registration algorithms have been proposed using various local feature detectors and descriptors (Gesto-Diaz et al., 2017; Sedaghat and Ebadi, 2015a, 2015b). Some examples have been mentioned in the following paragraphs.

Yuan et al. (2017) proposed a feature matching algorithm for poor textural images based on graph theory. Three detectors, including the SIFT, SURF and FAST algorithms, are used in their approach. Castillo-Carrión and Guerrero-Ginel (2017) proposed an optimized SIFT-based matching for multi-temporal aerial images. Konugurthi et al. (2016) proposed an automatic orthorectification of very high resolution remote sensing images using SIFT and genetic algorithms. Duan et al. (2016) proposed a combined image matching method for Chinese optical satellite imagery using the SIFT algorithm and a novel similarity measure, namely, DANCC (Distance, Angle and Normalized Cross-Correlation similarities). Schwind and d'Angelo evaluated the applicability of the BRISK algorithm for remote sensing image registration.

In many remote sensing applications, such as image fusion and change detection, the registration of multi-sensor remote sensing images is a vital process. However, robust multi-sensor remote sensing image registration is a difficult task due to non-linear intensity differences. The mutual information (MI) is robust to significant illumination differences and has been successfully applied in the registration of multi-sensor images (Gong et al., 2014; Suri