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Airplane detection based on rotation invariant and sparse coding in remote sensing images

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ABSTRACT

Airplane detection has been taking a great interest to researchers in the remote sensing filed. In this paper, we propose a new approach on feature extraction for airplane detection based on sparse coding in high resolution optical remote sensing images. However, direction of airplane in images brings difficulty on feature extraction. We focus on the airplane feature possessing rotation invariant that combined with sparse coding and radial gradient transform (RGT). Sparse coding has achieved excellent performance on classification problem through a linear combination of bases. Unlike the traditional bases learning that uses patch descriptor, this paper develops the idea by using RGT descriptors that compute the gradient histogram on annulus round the center of sample after radial gradient transform. This set of RGT descriptors on annuli is invariant to rotation. Thus the learned bases lead to the obtained sparse representation invariant to rotation. We also analyze the pooling problem within three different methods and normalization. The proposed pooling with constraint condition generates the final sparse representation which is robust to rotation and detection. The experimental results show that the proposed method has the better performance over other methods and provides a promising way to airplane detection.

1. Introduction

Target detection in high resolution optical remote sensing images is a challenging task owing to its changing appearance and arbitrary direction. More recently, airplane detection, as an important detected target, has gained hot research and exploration [1–3] in military and civil applications, such as airfield surveillance. With the resolution growing, more spatial information are provided so that we could know more about the feature information.

The problem of airplane detection is generally considered as exploiting target feature exclusively to make decision regarding the type of each sample–target or non-target, known as binary classification. Arbitrary direction of airplane in images brings difficulty on detection. The first need is to explore a robust feature that allows the airplane to be well discriminated without the influence by rotation. We focus on the issue of features for airplane detection on sparse coding. Sparse coding, as an emerging signal processing technique, has attracted more and more researchers' attention due to its comprehensive theoretical studies [4] and excellent performance on machine learning and computer vision problems [5,6].

The general sparse coding process consists of two-phase: dictionary learning and sparse representation. Local descriptors, such as scale invariant feature transform (SIFT) [7] descriptors or raw patches sampled from the image on a regular grid, are used to train dictionary for better fitting the data. The sparse representation uses the learned dictionary to find the best linear combination to represent the feature of the target. However, the general descriptor, such SIFT descriptor and HOG descriptor, dose not possess the rotation-invariant [8]. To obtain the rotation-invariant sparse representation, we apply radial gradient transform [8] descriptor to dictionary learning, thus the obtained sparse feature possesses the rotation-invariant property.

Several works have been done for airplane detection in the fields of remote sensing images, such as, shape-based method of circle frequency filter [9] uses the Fourier transform, and multiple segmentation [10] combining with contour information extracts candidate region. Xu and Duan [11] apply an artificial bee colony with an edge potential to recognition. Coarse-to-fine process prior [12] is proposed by using high-level information of the shape. All these methods are based on the gray image information and ignore gradient information that is robust to the local geometric changes. Thus we consider the gradient histogram on the samples, and also use the gradient information for dictionary learning and sparse representation.

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0030-4026/

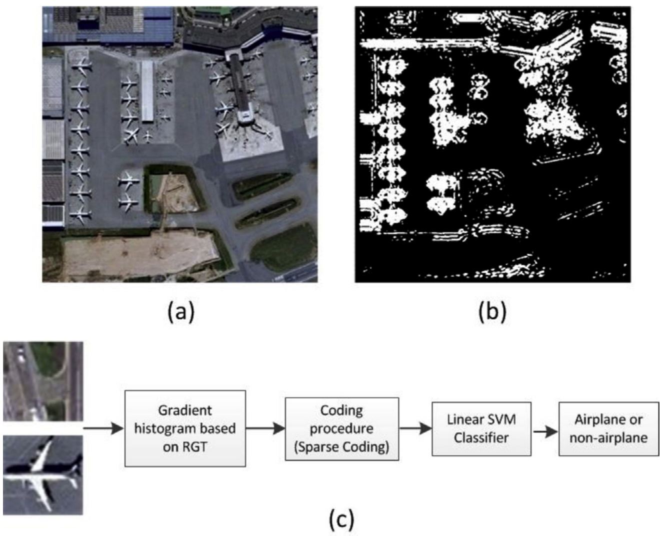

Fig. 1. (a) The remote sensing image with one-mater resolution. (b) The candidate region of airplane. (c) The workflow of airplane detection based on sparse coding and radial gradient transform (RGT) descriptor through linear classification. The two small images on the left are sampled from the candidate region of remote sensing image by using sliding window.

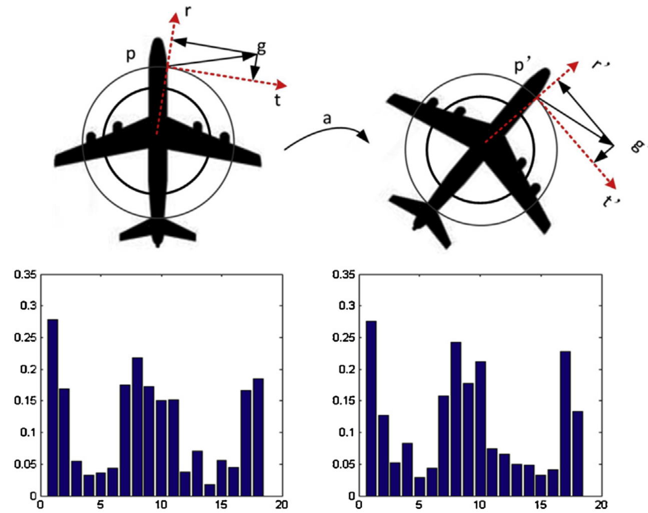

Fig. 2. Illustration of radial gradients. The first line: left: gradient **g** is projected onto radial coordinate system (r, t); right: the image rotates a certain angle α, the new gradient $\mathbf{g}'$, at the same position of airplane, projects onto new radial coordinate system (r', t'). The second line describe the gradient histogram based on annulus between two circles above. The x-coordinate is the 18 signed orientation bins; the y-coordinate is the gradient statistic information.

Orientation problem is the key problem in the airplane detection, because the orientation of the airplane is unpredictable within many remote sensing images. Thus we address the problem of rotation-invariant feature. Several methods have been applied to the rotation problem. Principal component analysis (PCA) method [13] estimates the main axis and uses template matching to detection; symmetry-based method [14] is to find the axis direction by minimum within-group variance dynamic threshold; and circle frequency filter [9] uses fourier transform to delete the influence of rotation. However, these methods are most based on pixel value, which could be affected by the various backgrounds of optical remote sensing images, such as illumination, shadowing, *etc.* Thus we consider the feature descriptor by using gradient information that is invariant to rotation after radial gradient transform [8].

This paper introduces a new rotation-invariant feature representation, based on sparse coding and radial gradient transform, which deals with arbitrary orientation of airplane in the high-resolution optical remote sensing images. We focus on the civil airports in remote sensing images from Google map and deal with the detection of civil airplane. The civil airplane in remote sensing images, which has 1-m resolution, possesses about 40 pixels length and 40 pixels width in such images, as shown in Fig. 1(a). Fig. 1(b) shows the candidate region of airplane by using circle frequency filter [9] method. The circle frequency filter could delete the rotation effect but poorly detect under complex background such that chosen as preprocess before detection. The workflow of the airplane detection is shown in Fig. 1(b). The radial gradient transform is the key process on computing the sparse feature. Local descriptors are formed on annuli based radial gradient transform system that possess rotation invariant. For the sparse coding, we first train the dictionary by using local descriptors that belong to all the samples. This obtained dictionary is more effective than the unsupervised one in terms of classification. We compare three pooling methods to obtain the final sparse representation by max, average and constraint. In the airplane detection, we take linear SVM as detection model due to its linear computation complexity.

This paper is organized as follows: In Section 2, we introduce the radial gradient transform. Sparse coding methods include dictionary learning and sparse representation are presented in Section 3. Section 4 argues about the pooling methods. Detection process and experiment results are shown in Sections 5 and 6, and concluding remarks are made in Section 7.

2. Rotation-invariant descriptors

The orientation of airplane is various according to the situation of the airport or some other condition. It is unrealistic to train all directions of airplanes to detect airplane in remote sensing images. The reasonable method is extracting feature of airplane possessing rotation-invariant. Typical feature descriptors, such as SIFT [7] and speeded up robust feature (SURF) [15], assign an orientation to interest points before extracting descriptor. But there are not always interest points in the airplane sample. So we need an orientation invariant descriptor which eliminates the computation of finding an orientation and interpolation the relevant pixels. In this section, we mainly discuss an orientation invariant descriptor based on radial gradient transform (RGT) [8], which will be used in sparse coding section.

2.1. Radial coordinate system

The general feature descriptor is based on gradient information. To make the gradient descriptor invariant to the varying orientation, we need to apply transformation to gradient information. RGT [8] projects gradient into the radial coordinate system without loss of information.

As shown in Fig. 2, radial coordinate system $(\mathbf{r}, \mathbf{t})$ is related to the point p and the center of the image, where vector $\mathbf{r}$ is the unit vector and its direction is from the center of image toward the point p. At the same time, unit vector $\mathbf{t}$ is orthogonal to vector $\mathbf{c}$. We decompose the gradient $\mathbf{g}$ onto radial coordinate system $(\mathbf{r}, \mathbf{t})$, which obtains a new vector $(\mathbf{g}^T\mathbf{r}, \mathbf{g}^T\mathbf{t})$. Assume the airplane is rotated with a certain angle. Point p turns to point p'. The gradients of these two points are different, but the amplitudes are the same. And then project the new point p' on the new radial coordinate system $(bfr', \mathbf{t}')$, which obtains another a new vector $(\mathbf{g}'^T\mathbf{r}',\ \mathbf{g}'^T\mathbf{t}')$. It is easy to verify that these two new vectors are equal:

$$(\mathbf{g}^T\mathbf{r},\ \mathbf{g}^T\mathbf{t}) = (\mathbf{g}'^T\mathbf{r}',\ \mathbf{g}'^T\mathbf{t}').$$