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A new framework for remote sensing image super-resolution: Sparse representation-based method by processing dictionaries with multi-type features

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ABSTRACT

Remote sensing images play an important role in many practical applications, however, due to the physical limitations of remote sensing devices, it is difficult to obtain images at an expecting high resolution level. Acquiring high-resolution(HR) images from the original low-resolution(LR) ones with super-resolution(SR) methods has always been an attractive proposition in embedded systems including various kinds of tablet PC and smart phone. SR methods based on sparse representation have been successfully used in processing remote sensing images, however, they have two major problems in common. First, they use only one type of image features to represent the low resolution(LR) images. However, one single type of features cannot accurately represent an image due to the diverse structures of the image, as a result, artifacts would be produced simultaneously. Second, many dictionary learning methods try to build a universal dictionary with only one single type of features. However, apparently, a dictionary with a single type of features is not enough to capture the different structures of a remote sensing image, without any doubt, the resultant image would turn out to be a poor one. To overcome the problems above, we propose a new framework for remote sensing image super resolution: sparse representation-based SR method by processing dictionaries with multi-type features. First, in order to represent the remote sensing image more accurately, different types of features are extracted from images. Second, to achieve a better performance, various dictionaries with multi-type features are learned to capture the essential structures of the image. Then, it's proposed to adaptively control the weights of the high resolution(HR) patches obtained by different dictionaries. Numerous experiments validate that this proposed framework brings better results in terms of both objective quantitation and visual perception than other compared algorithms.

1. Introduction

Every day, many remote sensing images are acquired by satellite, and they are of great importance in many practical applications, such as, defense, security surveillance, and aerospace. However, due to the physical limitations of remote sensing devices, it is difficult to obtain remote sensing images at an expecting high-resolution level. The fact, that remote sensing images are obtained at low spatial resolution, has always been one of the critical bottlenecks in many remote sensing applications, and it may lead to a failure in further analyses as well.

A straightforward way to obtain HR remote sensing images is to replace the LR imaging devices with HR ones. However, as a matter of fact, as soon as a satellite is launched, it is hardly possible to replace any device. Instead, acquiring HR remote sensing images by new technologies from LR ones becomes a more attractive proposition in embedded systems including various kinds of tablet PC and smart phone. SR method for remote sensing images, also as the topic of this paper, is one of the most prospective methods for those new technologies. One of its major advantages is that it enhances the image resolution in an embedded system without changing any hardware of the image acquisition system.

Super-resolution is cast as the inverse problem of recovering the original HR image from one or more LR images. Therefore, many algorithms have been proposed to improve it. Existing SR methods can be divided into three categories: interpolation-based ones, reconstruction-based ones, and single image ones. The interpolation-based methods [1–4] are the simplest and fastest methods to increase the image resolution; however the interpolation does not add any new detailed information into the enlarged image. What's worse, aliasing problems might happen at the same time.

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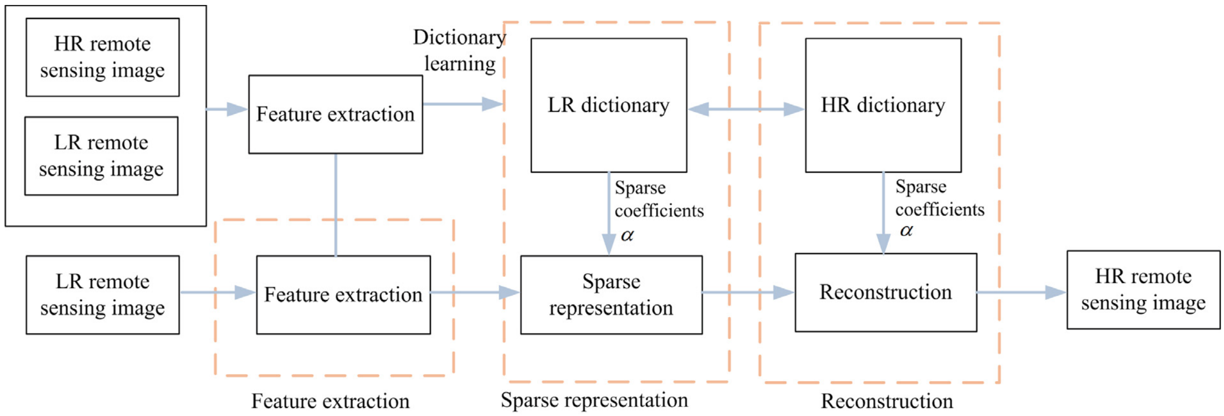

Fig. 1. Framework of sparse representation-based SR method.

Reconstruction-based methods [5–8] require different LR images of the same scene taken from slightly-moved viewpoints, and those LR images have different sub-pixel shifts from each other. This category of methods try to combine complementary information of different LR images to generate an HR one. However, it is quite difficult to capture several remote sensing images of the same scene in a moment. Besides, reconstruction-based methods are highly dependent on the performance of the registration method which aligns with different input images. Moreover, those methods use a priori knowledge of general image, such as smoothness of the image. This would result in that the reconstruction-based methods can deliver better performance with a small magnification factor, while they often fail to produce sufficient details at large magnification factors. All these limit the application of reconstruction-based methods for remote sensing image. Single image SR methods [9–19], which employ a training set containing LR and HR image pairs as external information source, can overcome the problems caused by reconstruction-based methods. They lie on the assumption that the missing high-frequency details can be predicted by the a prior co-occurrence between LR images and HR images in the training set. Therefore, with the help of the training set, they have a good performance and have become a popular topic in remote sensing image field.

Many technologies have been well adopted in single image SR methods. In [9], a Gaussian pyramid and Laplacian pyramid model is built, and the Bayesian theory is adopted to generate an HR image from the LR one. Similarly, the steerable pyramid model is generated, a Bayesian maximum a posteriori (MAP) problem would be solved with a pyramid parent structure and the best local match in [10]. In [12], contourlet transform and Markov network are employed to build a model for SR method, which can take the advantages of the both. In [11], a regression model between LR images and their corresponding HR images is built with kernel partial least squares. Sparse representation and dictionary learning methods have been widely used in image processing [20–28]. Recently, sparse representation-based SR methods [13–18] have proven to be effective in solving SR problems. In [16], a multi-scale dictionary is presented to make full use of the sparsity of the image. In [27], adaptive PCA-based sparse representations and non-local of images are explored to generate HR images. Most sparse representation-based methods assume that the HR and corresponding LR images(or patches) share the same set of sparse coefficients, thus the HR image can be reconstructed by combining the trained HR dictionary and the sparse coefficients of the LR image. The sparse representation-based SR methods can be realized by four stages: feature extraction, dictionary learning, sparse representation, and reconstruction, as shown in Fig. 1.

The feature extraction stage is to obtain essential features that can effectively represent the image. In this stage, the features of remote sensing images are extracted with filters to obtain feature maps. Then, overlapping feature patches are cropped from those feature maps [11]. The second stage builds an HR dictionary and its corresponding LR dictionary with the feature patches obtained in the first stage. The third stage is to sparsely represent the LR feature patches with the LR dictionary which is built in advance. The final stage is to reconstruct the HR patches by using the HR dictionary and the sparse coefficients of the corresponding LR patches. And finally the obtained HR patches are reunited into an HR remote sensing image.

The existing sparse representation-based SR methods for remote sensing image processing always have the following two main problems. The one is that they use only one single type of features to represent the remote sensing images. In other words, the image is described from only one aspect. However, there are always significantly various structures in one image, for example, the rivers usually distribute linearly while the islands in the same image are oval-shaped. So without any doubt, a single feature extraction approach would fail to represent the image accurately, which would generate artifacts in the resultant image. The other problem lies in that many dictionary learning methods aim at building a universal and over-complete dictionary with only one single type of features. However, one dictionary with one type of features makes it impossible to capture all the different structures of the remote sensing image. As a consequence, this would result in poor resultant images. To solve those problems, this study makes the following three main contributions.

1. Jointly representing an image with different types of features is proposed in feature extraction stage. For accurately representing different structures, remote sensing images (or patches) prefer to different types of features extracted by different approaches, since one single feature extraction approach cannot accurately capture the essential features of the image.
2. Multi-type feature dictionaries are exploited in sparse representation stage. Since one dictionary with single type of features is inadequate in capturing all of the different structures of the remote sensing image. To capture the different structures of the image more accurately, multi-feature dictionaries, which consist of different dictionaries with different features, are learned.
3. Multiple outputs, i.e., multiple HR patches can be estimated with multi-type feature dictionaries from one LR patch. To integrate those estimated HR patches, a strategy is proposed to adaptively adjust the weights of the HR patches from different dictionaries in the reconstruction stage.

The rest of this paper is organized as follows: Section 2 introduces the thesis of the sparse representation-based SR method while Section 3 presents the details of the proposed approach, then Section 4 reports the experimental results, and finally Section 5 draws the conclusion.