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A high accuracy land use/cover retrieval system

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KEYWORDS

Image retrieval; Land use; Content-based retrieval; Radial basis function; Super Resolution **Abstract** The effects of spatial resolution on the accuracy of mapping land use/cover types have received increasing attention as a large number of multi-scale earth observation data become available. Although many methods of semi automated image classification of remotely sensed data have been established for improving the accuracy of land use/cover classification during the past 40 years, most of them were employed in single-resolution image classification, which led to unsatisfactory results. In this paper, we propose a multi-resolution fast adaptive content-based retrieval system of satellite images. Through our proposed system, we apply a Super Resolution technique for the Landsat-TM images to have a high resolution for retrieval of satellite database images. We apply the backpropagation supervised artificial neural network classifier for both the multi and single resolution datasets. The results show significant improved land use/cover classification accuracy for the multi-resolution approach compared with those from single-resolution approach.

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1. Introduction

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One of the fundamental characteristics of a remotely sensed image is its spatial (x-y domain) resolution; as the basic infor-

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mation contained in the image is strongly dependent on spatial resolution [1]. Improper choice of different spatial resolution can lead to misleading interpretation, e.g. in a Landsat Multi-Spectral Scanner image, the urban residential environment is sensed as a relatively homogeneous entity. However, when observed at finer resolution, the residential area is mostly made of individual houses, roads and plants. With the development of new remote sensing systems, very-high spatial resolution images provide a set of continuous samples of the earth surface from local, to regional scales. The spatial resolution of various satellite sensors ranges from 0.5 to 25,000 m now. Furthermore, high resolution airborne data acquisition technology has developed rapidly in recent years. As an increasing number of high resolution data sets become available, there is an increasing need for more efficient approaches to store, process, and analyze these data sets. The development of efficient analysis methods of using these multiscale data to improve land use/cover mapping and linking thematic maps generated from high resolution to coarse resolution has become a challenge [2,3]. Several techniques have been employed to assess appropriate (or optimal) spatial resolutions. Although a particular classification can achieve the best result from a single resolution appropriate to the class, there is no single resolution which would give the best results from all classes [4]. Landscape objects (e.g. land cover/use polygons) are not the same size and vary in different structures. Some objects are better classified at finer resolutions while others require coarser resolutions. Therefore, as suggested by Ref. [1], various objects require different analysis scales according to the image scene model. Scene models may be either high (H) resolution with pixels smaller than objects, or low (L) resolution with pixels larger than objects to be mapped. From a practical standpoint, building a framework to represent, analyze and classify images represented by multiple resolutions is necessary in order to capture unique information about mapped classes that vary as a function of scale. Many previous studies show the importance of developing and evaluating spatial analytic methods and models to support multiscale databases [5-7].

The objective of this paper is to build a high accuracy content-based retrieval system of satellite images based on multiscale dataset. The used human-computer interactive system is based on relevance feedback. A large database of remotely sensed data has been used, which consists of 300 Landsat-7 TM satellite images scenes that cover different areas in Egypt and show land use/land cover [8]. By applying the Super Resolution (SR) techniques on this low-resolution Landsat TM dataset, a new high-resolution dataset has been restored. An improvement of the system accuracy has been achieved by applying the backpropagation supervised artificial neural network classifier for both the low and high resolution datasets.

In the next section we will give a brief description of the SR restoration technique used for creating the high resolution dataset. The proposed system will be presented in Section 3. In Section 4 we will demonstrate the used material and methodology. The classification results are shown in Section 5, and finally discussion and conclusions are given in Sections 6 and 7.

2. High resolution dataset

In general, multi-resolution images can be created in two ways: (1) by integrating different resolution images acquired by different sensors; and (2) aggregating fine resolution images into different coarse resolution levels (i.e., image pyramids). Obtaining images of different resolutions from different sensors could have advantage of including more spectral information that can be used to identify different objects, but is expensive. The miss-registration between different images also would increase the processing cost and reduce classification accuracy. It is more efficient to extract spatial information over a range of resolutions from a single high resolution image.

We will use in this paper, only two resolution levels datasets. First one is the low resolution Landsat-7 TM satellite images of different regions of Egypt, acquired on 6 May 1998, and 21 June 2001. Then we construct the second one (high resolution) by applying a SR technique on this dataset.

Super Resolution are techniques that in some way enhance the resolution of an imaging system. These SR-techniques break the diffraction-limit of the digital imaging sensor. There are both single-frame and multiple-frame variants of SR, where multiple-frame are the most useful. The basic idea behind Super-Resolution is the fusion of a sequence of low-resolution noisy blurred images to produce a higher resolution image or sequence. The information that was gained in the SR-image was embedded in the LR images in the form of aliasing. That is, LR images are sub-sampled (aliased) as well as shifted with sub-pixel precision. If the LR images are shifted by integer units, then each image contains the same information, and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different sub-pixel shifts from each other and if aliasing is present, however, then each image cannot be obtained from the others. In this case, the new information contained in each LR image can be exploited to obtain an HR image.

Generally to obtain different looks at the same scene, some relative scene motions must exist from frame to frame via multiple scenes or video sequences. Multiple scenes can be obtained from one camera with several captures or from multiple cameras located in different positions. These scene motions can occur due to the controlled motions in imaging systems, e.g., images acquired from orbiting satellites. The same is true of uncontrolled motions, e.g., movement of local objects or vibrating imaging systems. If these scene motions are known or can be estimated within sub-pixel accuracy, and if we combine these LR images, SR image reconstruction is possible [9,10].

The first step to comprehensively analyze the SR image reconstruction problem is to formulate an observation model that relates the original HR image to the observed LR images as follows

$$y_k = DB_k M_k X + n_k \quad \text{for } 1 \leqslant k \leqslant z \tag{1}$$

where X is the desired HR image and yk are the z LR images, M_k is a warp matrix of size $L_1N_1L_2N_2 \times L_1N_1L_2N_2$, B_k represents a $L_1N_1L_2N_2 \times L_1N_1L_2N_2$ blur matrix, D is a $(N_1N_2)^2 \times L_1N_1L_2N_2$ subsampling matrix, and n_k represents a lexicographically ordered noise vector.

Most of the SR image reconstruction methods proposed in the literature consists of the three stages illustrated in Fig. 1: registration, interpolation, and restoration (i.e., inverse procedure). These steps can be implemented separately or simultaneously according to the reconstruction methods adopted. The estimation of motion information is referred to as registration, and it is extensively studied in various fields of image processing. In the registration stage, the relative shifts between LR images compared to the reference LR image are estimated with fractional pixel accuracy. Obviously, accurate subpixel motion estimation is a very important factor in the success of the SR image reconstruction algorithm. Since the shifts between LR images are arbitrary, the registered HR image will not always match up to a uniformly spaced HR grid. Thus, nonuniform interpolation is necessary to obtain a uniformly spaced HR image from a nonuniformly spaced composite of LR images. Finally, image restoration is applied to the upsampled image to remove blurring and noise.

Using the nonuniform interpolation SR approach, which is the most intuitive method for SR image reconstruction [11,12], the low-resolution observation image sequence is registered, resulting in a composite image composed of samples on a nonuniformly spaced sampling grid. These non-uniformly spaced sample points are interpolated and re-sampled on the highresolution sampling grid (see Fig. 2). Applying this relatively Download English Version:

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