Competitive Segmentation Performance on Near-Lossless and Lossy Compressed Remote Sensing Images

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Abstract—Image segmentation lies at the heart of multiple image processing chains, and achieving accurate segmentation is of utmost importance as it affects later processing. Image segmentation has recently gained interest in the field of remote sensing, mostly due to the widespread availability of remote sensing data. This increased availability poses the problem of transmitting and storing large volumes of data. Compression is a common strategy to alleviate this problem. However, lossy or near-lossless compression prevents a perfect reconstruction of the recovered data. This letter investigates the image segmentation performance in data reconstructed after a near-lossless or a lossy compression. Two image segmentation algorithms and two compression standards are evaluated on data from several instruments. Experimental results reveal that segmentation performance over previously near-lossless and lossy compressed images is not markedly reduced at low and moderate compression ratios (CRs). In some scenarios, accurate segmentation performance can be achieved even for high CRs.

Index Terms—Image segmentation, JPEG 2000, JPEG-LS, lossy compression, maximum likelihood (ML), near-lossless compression, remote sensing data, successive band merging (SBM).

I. INTRODUCTION

IMAGE segmentation is generally defined as the process of partitioning an image into regions (or segments). The underlying idea consists of dividing an image into homogeneous segments by grouping the neighboring pixels that follow a similarity criterion. The main purpose is to estimate the structure of the scene and to extract image objects and boundaries for subsequent object-based analysis.

In the field of remote sensing, image segmentation is an essential step of low-level image analysis and is usually performed in the first stage of a processing chain [1].

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Efficiently segmented images are required in a wide variety of applications, such as object detection [2], land cover classification [3], or landscape change detection [4].

Advances in remote sensing technology have led to improve the quality of the harvested data in terms of spectral and spatial resolutions, and allowed to reveal more ground details. Segmentation results have thus been improved due to the rich information contained in the images. Several of the existing segmentation algorithms rely on two main traditional strategies: 1) region-based methods, which depend on region information, and 2) edge-based methods, which look for boundaries between objects to find them [5], [6]. Both strategies have proven to achieve competitive segmentation results.

However, improving the quality of the acquired data has also led to an increase in the size of the collected data, requiring more means for transmission and storage. Data compression is an effective way to reduce the volume of the collected data. Nonetheless, achieving high compression ratios (CRs) usually entails some level of distortion in the recovered scene, which may compromise the usefulness of the reconstructed data and prevent achieving good segmentation results. Texture blurring and unclear edges between objects can be a consequence of a near-lossless and lossy compression. These effects can make image segmentation a major challenge, because of the difficulties in detecting homogeneous regions or boundaries [7].

The impact of a near-lossless or a lossy compression stage on subsequent processes is lately receiving a lot of attention: in the scope of classification applications, different strategies to perform classification on previously compressed images were presented in [8]–[11]. Results revealed that the classification accuracy was still reliable after the compression stage, even at high CRs. Similar conclusions were yielded for anomaly detection [12], [13], for linear spectral unmixing [14], [15], and for statistical retrieval algorithms [16]–[18]. To the best of our knowledge, a similar study on the impact of compression on image segmentation has not been presented.

The aim of this work is to investigate the performance of image segmentation in remote sensing images reconstructed after a near-lossless or a lossy compression. This analysis, carried out in an early stage of the processing chain, can determine the usefulness of the data for subsequent processing (classification, detection, and so on). Segmentations on the reconstructed scenes are evaluated with respect to segmentations on the original scenes to determine the impact of compression.

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For a near-lossless compression, we employ the JPEG-LS standard [19], which has been widely used in the compression of high-resolution remote sensing data due to the speed and efficiency provided. For lossy compression, the JPEG 2000 standard [20] is employed, because it supplies a set of features that are important in the field of remote sensing, such as competitive low bit-rate (BR) performance, progressive quality image transmission, random codestream access, and so on. These features make both JPEG-LS and JPEG 2000 standards highly attractive in the context of remote sensing applications.

In the segmentation stage, two segmentation algorithms are employed: maximum likelihood (ML) [21] and successive band merging (SBM) [22]. ML is a simple segmentation technique, whose low computational complexity is suitable for remote sensing imagery. It has become an accepted estimate used as the baseline for more complex algorithms [23], [24]. SBM is a recent segmentation algorithm specifically designed for multispectral remote sensing images.

The remainder of this letter is organized as follows. Section II describes the compression techniques and the segmentation algorithms used in the experiments. Section III presents the data collection and the parameter setting. Section IV reports the experimental results. The conclusion is drawn in Section V.

II. METHODS

This section describes the segmentation techniques and the compression standards used in the experiments.

A. Segmentation Algorithms

For image segmentation, we use two methods: an algorithm based on the well-known ML approach and a novel method based on Markov random fields (MRFs), the SBM algorithm. Both methods have shown good performance on several remote sensing data sets [22], [25].

The ML algorithm computes the probability that a specific pixel belongs to a particular region. The algorithm assumes that the statistics for each region in the scene follow a normal distribution. Each pixel will be a part of the region that has the highest probability, considering that if the highest probability falls below a given threshold, then the pixel will not be assigned to any region. SBM is a segmentation algorithm devised to work with multispectral remote sensing images. The segmentation process is carried out through three stages. In the initial step, the maximizer of the posterior marginals (MPM) is estimated. In the second stage, contextual information is included in a nonparametric way. Finally, each pixel is assigned to a region in the scene [22].

B. Compression Standards

For image compression, we consider two paradigms: a near-lossless compression and a lossy compression. On one hand, near-lossless compression is used to control the maximum absolute error per sample introduced in the reconstructed data. On the other hand, lossy compression is employed to control the overall BR. Two standard coding techniques are employed in the experiments: JPEG-LS for near-lossless compression and JPEG 2000 for lossy compression. JPEG-LS is a lossless and near-lossless compression standard that provides simplicity, low computational complexity, and memory requirements. JPEG 2000 is an international standard that provides an extensive range of features in a single compressed bit-stream for a large amount of applications, such as remote sensing imagery, medical diagnostic imaging, and mobile communications, among others.

III. DATA AND EXPERIMENTAL SETTINGS

This section presents the data sets and the parameter configurations used in the experiments.

A. Data Collection

To conduct the experiments, 25 images from four different remote sensing instruments were studied. We selected images and ground-truth data devised for the testing of segmentation algorithms. In order to study a set of representative data, the tested data sets included images with different spectral and spatial resolutions and dissimilar number of spectral channels, obtained from different instruments and scanned on distinct scenarios. The scenes were captured over rural and urban areas and contain buildings, roads, grass, trees, crops, water, and railways, among other objects. Table I provides the characteristics of the data sets. Most of the images are public and available at [26] and [27].

B. Experimental Settings and Software

For near-lossless compression, the maximum absolute error per sample introduced in the data was controlled using seven peak absolute errors (PAE), \( \delta \in \{1, 3, 7, 15, 31, 63, 127\} \). Higher values of the PAE give rise to higher CRs, but the level of distortion introduced is also increased. For lossy compression, the overall BR was controlled using six target BRs, distributed between 4 and 0.1 bits per pixel per component (bpppc). It is expected that providing an analysis of the signal in terms of frequency components benefits the coding. Therefore, the wavelet transform was used to provide a more decorrelated and compact representation of the signal. In the experiments, six levels of the discrete-wavelet transform (DWT) were applied in the spatial dimension to exploit the spatial redundancy present in the scene.

The segmentation stage was carried out on the original and on the reconstructed data. Both the ML and the SBM algorithms were evaluated on the four data sets. To start the segmentation process, the selected algorithms needed an initial segmentation. All experiments started from an initial segmentation obtained from \( k \)-means [28]. Default options were used for the remaining parameters.
TABLE II
REGION AND CONTENT OF THE SCENES

| Instrument | Identifier | Region                      | Content                                                      |
|------------|------------|-----------------------------|--------------------------------------------------------------|
| AVIRIS     | Indian Pines | Rural area (Indiana)         | Alfalfa, corn, grass, wheat, woods, and buildings, among others |
| Landsat 8  | Humid Pampas | Rural area (Argentina)       | Wildfire, corn, fallow land, and water, among others         |
| QuickBird  | zh11       | Urban area (Zurich town)     | Roads, buildings, trees, grass, water, and railways, among others |
| ROSIS      | Pavia University | Urban area (Pavia town)   | Asphalt, meadows, trees, buildings, and shadows, among others |

Fig. 1. Segmentation performance in \( \hat{\kappa} \) (higher is better) for (Top) near-lossless compression and (Bottom) lossy compression. In the plots, the vertical axis represents the segmentation performance \( \hat{\kappa} \) and the horizontal axis represents the CR. Results using reconstructed data are plotted in solid lines and results using uncompressed data (original image) are plotted in dashed lines. Each mark represents the segmentation performance achieved when the scene has been previously compressed at a particular CR. Results for the ML algorithm are plotted in green lines and results for the SBM algorithm are plotted in blue lines. Each column shows results for a particular scene.

To achieve a fair comparison, the parameter configuration was kept constant for all compression and segmentation experiments, in such a way that we used suitable settings for the characteristics of all the images. The software implementations employed for compression were JPEG-LS software [29] for JPEG-LS and Kakadu software [30] for JPEG 2000. The segmentation stage (ML and SBM algorithms) was carried out using the Markov Model Toolbox [31] employed in [22].

IV. EXPERIMENTAL RESULTS

This section presents the experimental results. The proposed sequential chain includes first a compression stage. At the receiver side, the scene is decoded, and then image segmentation is carried out on the reconstructed data.

A. Segmentation Assessment

The segmentation performance was assessed with respect to handmade ground-truth segmentations. Following the strategy used in [22], we used Cohen’s kappa coefficients \( \hat{\kappa} \) [32] to compare the performance of the different schemes adopted. The \( \hat{\kappa} \) coefficient provides a measure of agreement between the machine segmentation and the human ground truth. Complete agreement corresponds to \( \hat{\kappa} = 1 \), and lack of agreement corresponds to \( \hat{\kappa} = 0 \).

Here, segmentation results are reported for four scenes (one from each data set). Results for the remaining images from each data set are similar. Table II provides characteristics for the scenes reported. Detailed experimental results for the 25 scenes described in Table I are provided as the Supplementary Material at http://gici.uab.cat/pub/coding_segmentation/.

Fig. 1 shows the segmentation performance for the near-lossless and lossy compression settings proposed. Plots show the \( \hat{\kappa} \) coefficients for different CRs when the ML and SBM algorithms are used in the segmentation stage. Results using original data (uncompressed) are also provided for comparison purposes. The relationship between PAEs/target BRs and CRs and the SNR energy achieved by each compression setting are reported in Table III. One can see that, for near-lossless, CRs of about 10:1 allow achieving at least the same segmentation performance as with the original data. Only the Indian Pines scene requires lower CRs of, approximately, 4:1 to keep the segmentation results unchanged when the SBM algorithm is employed. SBM uses the spectral information to obtain the most probable state of each pixel. When the CR increases, too much distortion may be introduced in the spectral dimension, which is reflected in the performance of the SBM algorithm.

In a lossy scenario, CRs of about 25:1 allow to retain enough features to achieve the same segmentation performance as with uncompressed data. As for the case of near-lossless compression, the Indian Pines scene begins to decrease the segmentation performance at a lower CR of, approximately, 8:1 when the SBM algorithm is employed. It is interesting to note that the ML algorithm achieves higher \( \hat{\kappa} \) coefficients than the SBM method when the spatial resolution of the scene is high and vice versa. While ML does not consider the relations between neighboring pixels, SBM does. If there are
TABLE III

FOR NEAR-LOSSLESS (PAE) AND LOSSY (TARGET BR) COMPRESSION, CR, bpppc, AND SNR ENERGY (IN DECIBEL) ARE REPORTED. THE DYNAMIC RANGE OF THE ORIGINAL IMAGE IS PROVIDED IN PARENTHESES. THE CORRESPONDING EXPERIMENTS FOR THE SEGMENTATION RESULTS REPORTED IN Fig. 2 ARE HERE MARKED IN ITALIC FONT

|            | Indian Pines (14 bpppc) | Humid Pampas (15 bpppc) | zh11 (12 bpppc) | Pavia University (13 bpppc) |
|------------|-------------------------|-------------------------|----------------|-----------------------------|
|            | CR | bpppc | SNR | CR | bpppc | SNR | CR | bpppc | SNR | CR | bpppc | SNR |
| 1          | 2.4:1 | 5.8 | 71.6 | 2.0:1 | 7.5 | 85.1 | 3.1:1 | 3.9 | 50.5 | 1.7:1 | 7.6 | 66.1 |
| 3          | 2.9:1 | 4.8 | 63.8 | 2.3:1 | 6.5 | 77.3 | 4.3:1 | 2.8 | 42.8 | 2.0:1 | 6.5 | 58.4 |
| 4          | 3.7:1 | 3.8 | 57.1 | 2.8:1 | 5.4 | 70.6 | 6.2:1 | 1.9 | 36.3 | 2.4:1 | 5.4 | 51.7 |
| 5          | 4.8:1 | 3.9 | 50.9 | 3.4:1 | 4.4 | 64.3 | 8.6:1 | 1.4 | 30.2 | 3.0:1 | 4.3 | 45.3 |
| 6          | 6.6:1 | 2.1 | 45.0 | 4.2:1 | 3.6 | 58.1 | 12.1:1 | 1.0 | 24.3 | 3.9:1 | 3.3 | 39.2 |
| 7          | 9.4:1 | 1.5 | 39.1 | 5.4:1 | 2.8 | 52.1 | 18.1:1 | 0.7 | 18.5 | 5.2:1 | 2.5 | 33.1 |
| 8          | 14.0:1 | 1.0 | 33.3 | 7.3:1 | 2.1 | 46.2 | 32.0:1 | 0.4 | 12.8 | 7.2:1 | 1.8 | 27.3 |
| BR         | 4          | 3.8:1 | 3.7 | 56.9 | 4.0:1 | 3.8 | 59.8 | 3.0:1 | 4.0 | 53.2 | 3.3:1 | 3.9 | 41.5 |
|           | 2          | 7.6:1 | 1.8 | 44.5 | 8.1:1 | 1.9 | 46.5 | 6.0:1 | 2.0 | 41.5 | 6.6:1 | 2.0 | 30.5 |
|           | 1          | 15.0:1 | 0.9 | 36.7 | 16.0:1 | 0.9 | 39.8 | 12.1:1 | 1.0 | 33.5 | 13.2:1 | 1.0 | 24.4 |
|           | 0.5        | 30.0:1 | 0.5 | 31.4 | 32.5:1 | 0.5 | 35.2 | 24.2:1 | 0.5 | 27.7 | 26.2:1 | 0.5 | 20.3 |
|           | 0.25       | 60.9:1 | 0.2 | 28.0 | 65.3:1 | 0.2 | 32.7 | 48.4:1 | 0.3 | 27.3 | 52.0:1 | 0.25 | 17.3 |
|           | 0.1        | 150.5:1 | 0.1 | 25.1 | 161.5:1 | 0.1 | 29.5 | 120.0:1 | 0.1 | 18.7 | 130.4:1 | 0.1 | 14.3 |

Fig. 2. Ground truth and segmentation results of the original and the reconstructed data. Each row shows a particular scene. Results are plotted for both the ML and SBM algorithms. The PAE/target BR used in the compression stage and the CR achieved are reported for each scene. The $\hat{\kappa}$ coefficient is reported for each segmentation.

no relations, the performance might decrease, which is likely to occur when the spatial resolution is high.

The reported results reveal that the segmentation performance over previously near-lossless and lossy compressed scenes is not markedly reduced at low and moderate CRs. Nonetheless, lossy compression allows keeping the segmentation results unchanged at higher CRs than the near-lossless compression. This is due to the different nature of
the distortion introduced by the near-lossless and the lossy compression. The impact of compression is the same for both the ML and SBM algorithms. Only in the case of the Indian Pines scene, the SBM algorithm is affected more significantly by compression than the ML algorithm.

Fig. 2 shows the handmarked ground truth employed to assess the segmentation performance and some segmentation results for the ML and SBM algorithms. This figure shows the segmented images when the original scene and the reconstructed data from the near-lossless and the lossy compression are used in the segmentation stage. For reconstructed data, the higher CR that allows achieving competitive segmentation performance for both the ML and SBM algorithms is displayed.

V. CONCLUSION

In this letter, the performance of image segmentation on scenes that had gone through a compression and a decompression stage was investigated. In the compression stage, the JPEG-LS and the JPEG 2000 standards were used to perform a near-lossless and a lossy compression, respectively. Image segmentation was carried out using the ML and SBM algorithms.

Experimental results revealed that low and moderate CRs do not reduce the performance of the segmentation algorithms when the reconstructed data are used. Near-lossless compression allowed producing the same segmentation performance as with the original data at a CR of, approximately, 10:1. For lossy compression, unchanged segmentations were achieved at a CR of, approximately, 25:1. The impact of compression was similar for both the ML and SBM algorithms and the different scenarios analyzed. Only in the case of the Indian Pines scene, segmentation results remained unchanged at CRs of 4:1 and 8:1 for the near-lossless and the lossy compression, respectively, when the SBM algorithm was used. These observations are consistent with similar results reported for other scientific areas and may benefit the development of upcoming remote sensing instruments, image processing chains, and image analysis applications.

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