Abstract—Content-based image retrieval (CBIR) systems have gained significant importance in the remotely sensed hyperspectral imaging community due to the increasing availability of hyperspectral data collected from different instruments. Spectral unmixing has been a popular technique for not only interpreting hyperspectral images but also retrieving them precisely from databases based on information content. This is due to the fact that the information provided by unmixing (i.e., the spectrally pure components of the scene or endmembers, and their corresponding abundance fractions) provides a very intuitive way to describe the content of the scene in both the spectral and the spatial sense. In this letter, we present a new computationally efficient CBIR system for hyperspectral data (available online: http://hypercomp.es/repositorySparse) which uses sparse unmixing concepts to retrieve hyperspectral scenes, based on their content, from large repositories. The search is guided by a spectral library, which is used as a guide to retrieve the data in a robust and efficient way. Given the large size of libraries and the sparsity of the unmixing solutions, the incorporation of sparse unmixing to the CBIR engine brings significant advantages. To optimize its performance in computational terms, the system has been implemented in parallel by taking advantage of the computational power of commodity graphics processing units. The proposed system is validated using a collection of synthetic and real hyperspectral images, exhibiting state-of-the-art performance.

Index Terms—Content-based image retrieval (CBIR), graphics processing units (GPUs), hyperspectral imaging, sparse unmixing.

I. INTRODUCTION

Over the last years, hyperspectral remote sensing sensors have collected a large amount of data from different locations, and there are several new missions under development [1]. Hence, the incorporation of context-based content retrieval (CBIR) [2] techniques into remote sensing data repositories offers significant advantages from the viewpoint of effectively managing, storing, and retrieving large volumes of remotely sensed data. Spectral unmixing [3], [4] has been shown to be effective in the task of not only interpreting hyperspectral images but also retrieving them from databases [5].

For instance, a spectral/spatial CBIR system for hyperspectral images was described in [6] which exploits endmembers (spectrally pure signatures [3], in spectral unmixing jargon) and per-pixel endmember abundance fractions. These sources of information are integrated into a dissimilarity measure that guides the search for answers to database queries [7]. In this context, each hyperspectral image can be characterized by a tuple given by the set of extracted endmembers and the set of fractional abundance maps resulting from an unmixing process conducted using three stages [8].

A similar strategy is employed in [9], which presents a parallel heterogeneous CBIR system for efficient hyperspectral image retrieval using spectral mixture analysis. This system extracts endmembers and estimates abundances from each image of the database and from an example image used for searching. Therefore, the query is designed to compare the spectral information of an example image for searching to that of the images from the database. In addition, the system is efficiently implemented for heterogeneous networks of computers, possibly distributed among different locations.

Recently, Sevilla and Plaza [2] presented a web-based system which manages a digital repository of hyperspectral image data, allowing for the upload and retrieval of images through a CBIR engine based on spectral unmixing concepts. The system has been efficiently implemented in parallel using graphics processing units (GPUs) [5]. The techniques used to implement the CBIR engine are based on the extraction of endmembers directly from the available scenes, which presents some challenges.

1) First, if the spatial resolution of the sensor is not high enough to separate different pure-signature classes at a macroscopic level, the resulting spectral measurement can be a composite of individual pure spectra which correspond to materials that jointly occupy a single pixel. In this case, the use of image-derived endmembers may not result in accurate fractional abundance estimations since, in this case, it is likely that such endmembers may not be completely pure in nature.

2) Second, mixed pixels can also result when distinct materials are combined into a microscopic (intimate) mixture, which is independent from the spatial resolution of the sensor. In this scenario, the use of image-derived spectral
endmembers again cannot accurately characterize intimate spectral mixtures.

To address these issues, in this letter, we propose a solution based on sparse unmixing techniques [10], which take advantage of the increasing availability of the spectral libraries collected in optimal conditions (e.g., in a laboratory). The proposed system (available online at http://hypercomp.es/repositorySparse) uses sparse unmixing methods in order to perform the retrieval of images stored in the database, using spectral libraries to guide the search. In this way, the abundance maps are estimated for each image in the database using the library signatures as endmembers. This results in a sparsity map for each image, which collects the fractional abundance estimations obtained for each spectral signature of the library in the scene. The CBIR is then conducted based on the sparsity map, which provides a unique fingerprint for each scene. This approach has several advantages.

1) First and foremost, the need to estimate the number of endmembers and the endmember signatures (required in traditional spectral unmixing techniques [3]) is no longer present in our context, as the endmembers are selected from the available library. This semisupervised approach simplifies the searching process, which is based on ideal endmembers already available a priori.

2) Second, in order to catalog a new scene for storage in the system, we just need one execution of the considered sparse unmixing algorithm, while other CBIR systems based on unmixing such as [6] and [9] require executing a full spectral unmixing chain (made up of three stages: the estimation of the number of endmembers, the estimation of the endmember signatures, and the estimation of abundances). This greatly simplifies the cataloging procedure of new scenes in the CBIR engine.

3) Third, in order to increase the computational efficiency of the system, we have used GPUs (as in [5]) to accelerate the different parts of the CBIR system (cataloging and retrieval of scenes). Sparse unmixing techniques are amenable for parallel implementation on GPUs [11], which allows using these inexpensive hardware accelerators to increase the computational performance of our system.

This letter is structured as follows. Section II describes the proposed system and the way that it performs queries to the database through the designed web interface. Section III provides a comparison of the proposed CBIR system based on sparse unmixing with the system described in [2], implemented using traditional (linear) spectral unmixing instead of sparse techniques. Here, we analyze the retrieval accuracy of the system (using real and synthetic hyperspectral scenes simulated with different noise levels) and also the computational efficiency of the GPU implementations. Section IV concludes this letter with remarks and plausible future research lines.

II. SPARSE UNMIXING-BASED CBIR SYSTEM

The overall workflow of the proposed system is illustrated in Fig. 1. As shown by Fig. 1, a first important component in the system is the adopted spectral library, which should have equal or higher spectral resolution than that of the images stored in the database. We have implemented a spectral convolution strategy that looks for wavelengths which are present in both the hyperspectral data and the input spectral library (with the possibility to include a tolerance threshold in the wavelength matching procedure). In this way, the library signatures are adapted to the analyzed images, which means that the spectral signatures of those signatures have as many spectral bands as those in the images that have been matched in the procedure.
A second important component in our system is the selection of computing resources in which the cataloging of a new image will take place or in which the query process will be computed. Currently, the system is supported by two clusters of GPUs, one available at CETA-Ciemat in Trujillo, Spain,\(^1\) and another available at the University of Timisoara, Romania.\(^2\) This means that the unmixing operations can be executed in parallel in GPU clusters, taking advantage of their enhanced computational power and memory availability for processing large collections of data. As shown by Fig. 1, when conducting a query, it is possible to filter the best results by applying a constraint based on a minimum abundance percentage. Such filter is implemented by calculating the total abundance of each of the endmembers in the scene and summing all the relative contributions in each pixel.

Once the aforementioned elements have been established, our CBIR system executes a sparse unmixing algorithm to obtain a set of endmembers (which are selected from the input library) as well as their corresponding abundance maps. The algorithm that we have used for this purpose is the spectral unmixing by splitting and augmented Lagrangian (SUNSAL), introduced in [12]. This method solves a linear sparse regression problem using the alternating direction method of multipliers (ADMM). SUNSAL is an instance on ADMM, which decomposes a difficult problem into a sequence of simpler ones, resulting in a very fast method. A GPU implementation of SUNSAL has been presented in [11]. In this implementation, the most time-consuming operations (most of them inside a loop) are performed in the GPU by the maximum exploitation of the architecture characteristics. On the other hand, the simplest operations (i.e., small matrix inversions) are executed in the CPU.

As shown by Fig. 1, the results of sparse unmixing (i.e., endmembers and abundances) are used to query the database. This is performed using the GPU architecture to accelerate the query process by means of the compute unified device architecture (CUDA).\(^3\) The software architecture has been developed using Symfony2, a full-stack web framework, and the database system adopted is MySQL.\(^4\) Each query returns a set of candidate endmembers (selected from the metadata of the images that are initially selected by the query). Then, the images are filtered by using spectral comparison metrics (based on a spectral angle distance (SAD) threshold and possibly refined by an additional abundance tolerance threshold that can be used, for instance, to discard images in which the presence of a given endmember is spurious or not sufficiently representative in the scene). The outcome of the query process is a set of the most similar hyperspectral scenes identified in the database, ranked according to the aforementioned criteria.

The main innovations of the system interface with regard to the system presented in [2] are related with the execution of the sparse unmixing algorithm and the management of the resulting sparsity maps. The cataloging interface now allows an end user to select a sparse algorithm (one available at the moment) and also the cluster of computers in which the algorithm will be executed. Then, the results are retrieved by the system and stored in the database. The system allows repeating this process several times, and the user needs to select the best results to be included in the query process. The interface also allows to review the obtained results and even to download them. Our system has been tested for more than 20 concurrent users without problems.

### III. Experiments and Results

The performance of the proposed sparse CBIR system has been evaluated from two different perspectives: its ability to retrieve hyperspectral images of interest from the set of cataloged ones available in the system, and the efficiency in cataloging new hyperspectral images to be stored in the repository. In addition, we compare the results of the sparse CBIR with the unmixing CBIR approach in [2], which is based on the identification of image-derived endmembers. Since the system in [2] allows constructing different hyperspectral unmixing chains, we have selected the most accurate and computationally efficient one in the experiments reported in [2], which is made up of the virtual dimensionality [13] for the estimation of the number of endmembers, an orthogonal subspace projection with Gram–Schmidt orthogonalization [14] for the identification of image-derived endmember signatures, and the image space reconstruction algorithm [15] for the estimation of abundances.

#### A. Hyperspectral Data

A collection of 35 synthetic hyperspectral images is used for validation. These scenes are composed of known pure spectral signatures with different noise levels, synthesized from spectral signatures extracted from the the U.S. Geological Survey (USGS) spectral library [16]. The procedure for constructing the images is described in [2]. The database consists of five types of fractal images with seven different signal-to-noise ratios (SNRs) ranging between 10:1 and 110:1. In all cases, the images contain nine endmembers randomly selected from the USGS library, and their spectral resolution is of 221 spectral bands between 0.4 and 2.5 μm, with 100 × 100 pixels per scene.

The real data stored in the repository comprise several full flight lines comprising various gigabytes of data. Out of them, we highlight the Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS) Cuprite scene, due to the fact that this scene has been widely used for spectral unmixing purposes and can be directly related to the USGS digital spectral library as it contains several of the minerals characterized in the library.

#### B. Evaluation of Retrieval Accuracy

An important advantage of the proposed sparse CBIR system with regard to the system presented in [2] is that the images are cataloged using endmembers obtained from a library instead of endmembers derived from the image scene. As a result, the SAD [3] scores are always very low when conducting a spectral-based search. For illustrative purposes, Table I shows the SAD results obtained using the system presented in [2] for the considered synthetic and real scenes. All these results are improved by the proposed system, as the SAD-based results obtained using sparse unmixing are always very close to zero. As shown by Table I, the previous version of the system has some cases (particularly for the real AVIRIS Cuprite scene) in which the SAD scores are nonoptimal, resulting from the spectral difference between the image-derived endmembers and

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2https://hpc.uvt.ro/infrastructure/host-gpu-cluster/
4http://www.mysql.com
TABLE I

<table>
<thead>
<tr>
<th>USGS signature</th>
<th>Signal to noise ratio</th>
<th>AVIRIS Cuprite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kaolinite CMB</td>
<td>12.511</td>
<td>1.251</td>
</tr>
<tr>
<td>GDS48</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>Mica (0.003)</td>
<td>0.349</td>
<td>0.349</td>
</tr>
<tr>
<td>Pyrophyllite</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>FVS0</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>Sphene</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>TiO2</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>Goethite</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>KGeO (0.003)</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

TABLE II
ROOT MEAN MEAN RECONSTRUCTION ERROR (RMSE) IN ABUNDANCE ESTIMATION AFTER COMPARING THE RESULTS PROVIDED BY THE UNMIXING-BASED CBIR SYSTEM IN [2] AND THOSE OBTAINED BY THE SPARSE-BASED CBIR SYSTEM USING THE SYNTHESTIC DATA

<table>
<thead>
<tr>
<th>USGS signature</th>
<th>CBIR Approach</th>
<th>Signal to noise ratio</th>
<th>AVIRIS Cuprite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kaolinite CMB</td>
<td>Unmixing</td>
<td>0.097</td>
<td>0.097</td>
</tr>
<tr>
<td>GDS48</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Mica</td>
<td>0.001</td>
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<tr>
<td>KGeO (0.003)</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

In our previous version of the system, described in [2] and which does not use sparse unmixing concepts, we used the similarity to the spectral library endmembers as a criterion to establish a ranking of the retrieved images. However, in this version, we use the spectral library signatures to catalog the scene as metadata (instead of the endmembers derived from the image), and as a result, the results of spectral matching are no longer appropriate for establishing the ranking as many of the spectral comparisons provide a spectral angle of zero, meaning that the endmembers in the library used for searching purposes are present in the metadata used to catalog a given scene. Therefore, in this version, we use the root-mean-square error (RMSE) as a criterion to evaluate if the materials in the library are really contained in the image.

For the synthetic scenes, we have specifically used the RMSE in abundance estimation [3] since we have ground-truth abundance maps. This metric can be seen as another indicator of the quality of the conducted unmixing process to catalog a new scene in the system. In this case, it is generally expected that the RMSE scores obtained in abundance estimation using image-derived endmembers are sensibly lower than those obtained using external library endmembers, as the endmembers in the former case come directly from the scene. However, Table II reveals that the RMSE scores obtained in the estimation of abundances for the synthetic scenes by the sparse CBIR system do not differ significantly from those obtained using the unmixing CBIR system which uses image-derived endmembers. It should be noted that the RMSE could not be obtained for real scenes such as the AVIRIS Cuprite scene since the ground-truth abundances are not available in practice. However, in this case, we calculated the RMSE between the original and the reconstructed scene using the endmembers and the abundances derived by the two compared CBIR systems. Again, the differences were not very significant, with an RMSE of 0.190 when the unmixing-based CBIR system in [2] was used and that of 0.332 when the sparse CBIR was used. This indicates that sparse unmixing can be also used effectively in this context.

C. Evaluation of Parallel Performance

The computational performance of the proposed CBIR system has been evaluated using both CPU and GPU architectures available in two different clusters. The serial algorithms were executed in one of the available cores of a multicore CPU of type Quad Core Intel Xeon at 2.26 GHz with four physical cores and 24 GB of DDR3 SRAM memory. On the other hand, the parallel algorithms were performed in a cluster of 44 GPUs with NVidia™ TESLA M2070Q GPU devices mounted in a system with two-multicore Quad Core Intel Xeon at 3.46 GHz with four physical cores and 32 GB of DDR3 SRAM memory. Before describing our results, it is important to emphasize that our GPU implementations provide exactly the same results as the serial versions of the algorithms, implemented using the gcc (gnu compiler default) with optimization flag −O3. All our reported results include the mean values and the standard deviations measured across ten algorithm executions.

Table III shows the processing times (in seconds) obtained by the proposed sparse CBIR system when cataloging the AVIRIS Cuprite scene and a synthetic scene using the entire USGS spectral library of minerals (comprising 481 signatures). In the table, we display the CPU and GPU times (including the initialization time required in the GPU cluster) and the speedup of the GPU version over the CPU one. As shown by Table III, the GPU version shows significant speedups. Table IV shows the timing and speedups obtained by the sparse CBIR system when
are acquired in ideal conditions, this allows for a more reliable process for the generation of metadata and image retrieval, circumventing problems related to the mixture problem that have traditionally prevented the extraction of completely pure spectral signatures from hyperspectral images. The sparse CBIR approach also allows for a more robust catalog since the metadata is not generated from a given image instance but from a previously available spectral library with high-quality spectral signatures measured in ideal conditions. As future extension of the system, we will include other efficient implementations of sparse unmixing algorithms and exploit other strategies for GPU optimization, such as parallel streams. In addition, we are working toward including the possibility of performing queries based on the abundance of a given material in the database for future developments of the system.

### IV. Conclusions and Future Lines

In this letter, we have described a CBIR system which takes advantage of sparse unmixing techniques for the process of cataloging and retrieving hyperspectral scenes from large hyperspectral repositories. The use of sparse unmixing offers an important advantage: The generation of metadata and the CBIR process can be guided by a spectral library of laboratory-measured endmembers instead of endmembers extracted from the hyperspectral image. Since the endmembers in the library conducted the cataloging process over the AVIRIS Cuprite scene using different numbers of signatures in the USGS library. As shown by Table IV, the cataloging times (and speedups) increase notably with the number of spectral signatures used in the library. These results can be compared with those reported in [2], in which the unmixing chain used to catalog the AVIRIS Cuprite scene took 4.012 s in the same GPU architecture. These results suggest that the sparse CBIR system implemented in GPUs is more computationally effective, particularly for a very large number of spectral signatures. Moreover, the sparse CBIR system can obtain all the needed information relevant to a query in just one execution, while the unmixing-based approach in [2] needs to execute several algorithms (which includes several downloading/uploading transactions).

### REFERENCES