Mining Multiple Satellite Sensor Data Using Collaborative Clustering

Germain Forestier, Cédric Wemmert, Pierre Gancarski
University of Strasbourg - LSIIT - CNRS UMR 7005
Pole API, Bd Sebastien Brant
67412 Illkirch - France
{forestier,wemmert,gancarski}@unistra.fr

Jordi Inglada
CNES - DCT/SI/AP - BPI 1219
18, avenue Edouard Belin
31401 Toulouse Cedex 9 - France
jordi.inglada@cnes.fr

***Abstract*—In recent years, satellite sensor data have become easier to acquire. Several different satellite systems are now available and produce a large amount of data used for Earth observation. To better grasp the complexity of the Earth surface, it became usual to use different images from different satellites. However, it is generally difficult to predict the potential gain of using multisource satellite sensor data before actually acquiring the data. In this paper, we present a simulation approach to create different views of remote sensing sensor data according to different satellite characteristics. These different views are then used in a collaborative clustering approach to assess the interest of using these multisource data together. Experiments provide some insights on couple of satellite systems able to leverage the complementary of the sources.**

***Index Terms*—clustering, multisource data, remote sensing**

I. Introduction

Nowadays, a large amount of different satellites are available to capture remote sensing images of the Earth surface. These remotely sensed data are intensively used for Earth observation and satellite systems are employed for gathering data in the fields of agriculture and food production, geology, oil and mineral exploration, geography and urban to non-urban localities. Each satellite has its own characteristics, the most important being its spectral resolution. The spectral resolution of a sensor can be characterized by the number of spectral bands, their bandwidths and their localizations along the spectrum [1]. Several previous studies [1], [2], [3] showed that the spectral resolution is a critical issue, especially to discriminate different land covers in complex environment like urban areas. In spite of the increasing availability of hyperspectral data, multispectral optical sensors on board of several satellites are acquiring everyday a massive amount of data with a relatively poor spectral resolution. Most of multispectral systems have 4 to 7 spectral bands within the visible to middle infrared region of the electromagnetic spectrum [4]. There exist however some systems that use one or more thermal infrared bands. One of the main advantage compared to hyperspectral acquisition, is the larger spatial coverage, which allows a faster and wider mapping of large areas. Indeed, satellite remote sensing systems provide both, a synoptic view space and economies of scale [4].

As the number of different available satellite systems increases along with the complexity of the data to classify, one of the big challenge is to assess the complementarity of the sensors for a given application. Indeed, the information provided by different satellite sensors might be complementary, and a key issue is to design systems able to use these heterogeneous information sources in a single process. However, acquiring these images is still very costly, that is why it could be interesting to *a priori* assess the complementary of the sensors. To address this issue, we used in this paper a sensor simulation approach. Sensor simulation, also called band simulation or band synthesis, consists in generating simulated multispectral spectra from data acquired by existing sensors, with higher spectral resolution. This simulation consists in combining narrow hyperspectral bands into broader multispectral bands. This kind of approach has already been used, especially for sensor calibration and sensor simulation. The spectra simulation step uses the Relative Spectral Response (RSR) functions of the multispectral sensor, which describes the spectral response of each simulated sensor's band. The spectra used for the simulation were extracted from a spectral library which is a repository of spectra of various kinds of materials (e.g. mineral, man-made material, vegetation…) generally captured *in situ* using field instruments. We used this library along the various sensor characteristics to simulate datasets for different satellites available on the market. In order to mine these multisource data and to assess the use of multiple sources, we used a collaborative clustering approach.

Collaborative clustering [5] has been originally used to make collaborate different clustering methods working on the same dataset. Consequently, the goal was to use the information provided by each clustering method to improve the clustering of a single and common dataset. In this paper, we address the problem of multiple data sources clustering using the collaborative clustering paradigm. Indeed, while most data mining algorithms are conceived for mining a single data source, collaborative clustering is naturally able to handle data from multiple sources. Furthermore, each data source can be handled by a different algorithm specifically chosen to cluster each specific source. Forestier et al. [6] already used collaborative clustering to mine multisource remote sensing data. However, they only used already acquired images. In this paper, we present a way to simulate sensor's data without actually having to acquire the images. This approach allows us to easily compare more satellite systems and to gain some insights on which satellite sensor to use for a specific application.

The rest of the paper is organized as follows. Section 2 presents an overview of collaborative clustering. Section

3 gives more details on the sensor simulation approach. In Section 4, the different experiments are presented, and Section 5 concludes the paper.

II. Multisource collaborative clustering

Given a set of different clustering results, the goal of collaborative clustering is to find a consensus among these different results by reducing the disagreements between the different results of the ensemble. To identify and solve the conflicts between the clusters of the different results, the similarity of the clusters from the different results has to be evaluated. Consequently, we have to design a *local similarity* measure capable to compare two clusters from two different results. This measure will then be used to identify the couples of clusters (of two different results) having a poor similarity (i.e. sharing a poor overlap of data objects). These couples will define the conflicts to solve to increase the similarity between the results.

Moreover, we also have to estimate the *global similarity* of all the clusterings involved in the collaboration to be able to assess the global usefulness of a local modification. Indeed, a conflict is identified between a couple of results whereas more than two methods can be involved in collaboration process. Consequently, modification at the local level (i.e. between a couple of results) has to be assessed at a global level (i.e. all the results involved in the collaboration). The goal of collaborative clustering is to maximize this global similarity which is an indicator of the agreement among the set of results.

A. Local clusterings comparison

A large number of criteria exist to evaluate the similarity between two clustering results. However, these criteria only give a global evaluation of the similarity between two partitions. As we want to identify exactly which clusters are involved in the conflict, we need to compare each cluster of one result with all the clusters of the other results. In order to compare a couple of results, we use the confusion matrix or matching matrix (1).

Let $\breve{\mathcal{R}} = \langle \mathcal{R}^i \rangle_{i=1\ldots m}$ be the set of m results and $\langle C_k^i \rangle_{k=1\ldots n_i}$ be the n_i clusters of $\mathcal{R}^i$. This set is composed of clustering results created with different algorithms or the same algorithm with different parameters.

The *matching matrix* $\mathcal{M}^{i,j}$ between two results $\mathcal{R}^i$ and $\mathcal{R}^j$ is a $n_i \times n_j$ matrix defined by:

$$\mathcal{M}^{i,j} = \begin{pmatrix} \alpha_{1,1}^{i,j} & \ldots & \alpha_{1,n_j}^{i,j} \\ & \vdots & \\ \alpha_{n_i,1}^{i,j} & \ldots & \alpha_{n_i,n_j}^{i,j} \end{pmatrix} \text{ where } \alpha_{k,l}^{i,j} = \frac{\left|C_k^i \cap C_l^j\right|}{\left|C_k^i\right|} \quad (1)$$

The *adequacy* $\omega_k^{i,j}$ of a cluster C_k^i compared to a clustering $\mathcal{R}^j$ is evaluated by observing the intersection (1) between the cluster C_k^i and its corresponding cluster (i.e. the most overlapping cluster) in $\mathcal{R}^j$, and by taking into account the distribution $\rho_k^{i,j}$ (3) of the cluster C_k^i in all the clusters of $\mathcal{R}^j$:

$$\omega_k^{i,j} = \rho_k^{i,j} \alpha_{l,k}^{j,i} \quad (2)$$

where $\alpha_{l,k}^{j,i} = max\langle \alpha_{l,k}^{j,i} \rangle_{l=1\ldots n_j}$ and

$$\rho_k^{i,j} = \sum_{r=1}^{n_j} (\alpha_{k,r}^{i,j})^2 \quad (3)$$

To compute the *local similarity* between two results, the adequacies of each couple of clusters of the two results are averaged. The similarities have to be computed in each of the two ways, as the matching matrices are not usually symmetric ($\omega_k^{i,j} \neq \omega_k^{j,i}$).

However, if we try to only maximize the local similarity of the results, we could easily end up with a trivial (and not wanted) solution like a unique cluster with all the data objects inside it. To cope with this problem, we introduce an evaluation of the quality of the two clusterings in the local similarity measure as follows:

$$\gamma^{i,j} = \frac{1}{2} \left(\underbrace{\left(\frac{1}{n_i} \sum_{k=1}^{n_i} \omega_k^{i,j} + \frac{1}{n_j} \sum_{k=1}^{n_j} \omega_k^{j,i} \right)}_{\text{similarity}} + \underbrace{\left(\delta^i + \delta^j \right)}_{\text{quality}} \right) \quad (4)$$

where δ^i is a measure of the quality of a result $\mathcal{R}^i$. This measure depends on the algorithm used in the process. Any partition validity index can be used here, like compacity, Silhouette [7] or Davies Bouldin [8]. Furthermore, if the user has some knowledge about the number of expected clusters, a penalty measure can be introduced. If more background knowledge is available like labeled objects or constraints, this measure can also leverage this information.

B. Global clusterings comparison

The local similarity (4) evaluates the similarity and the quality of a couple of results. Though, more than two methods can be involved in the collaboration process. The *global similarity* evaluates the similarity of each couple of results involved in the collaboration and gives a global assessment of the results similarities:

$$\Gamma = \frac{1}{m} \sum_{i=1}^{m} \Gamma^i \quad (5)$$

where

$$\Gamma^i = \frac{1}{m-1} \sum_{\substack{j=1 \\ j \neq i}}^{m} \gamma^{i,j} \quad (6)$$

C. Conflict definition and assessment

There is a *conflict* between two clustering results $\mathcal{R}^i$ and $\mathcal{R}^j$ about the cluster C_i^k of $\mathcal{R}^i$, if there is no cluster in $\mathcal{R}^j$ similar to C_k^i. Each conflict $\mathcal{K}_k^{i,j}$ is therefore identified by one cluster C_k^i and one result $\mathcal{R}^j$. Its importance $CI\left(\mathcal{K}_k^{i,j}\right)$ is computed according to the local similarity between C_k^i and $\mathcal{R}^j$ (2) as:

$$CI\left(\mathcal{K}_k^{i,j}\right) = 1 - \omega_k^{i,j} \quad (7)$$

The list of conflicts $\breve{\mathcal{K}}$ containing all the conflicts of a set of results $\breve{\mathcal{R}}$ is defined by:

$$\breve{\mathcal{K}} = \texttt{conflicts}(\breve{\mathcal{R}}) \tag{8}$$

where the method `conflicts` computes the conflicts of the set of results $\breve{\mathcal{R}}$. Each conflict has an importance (7) and involves a couple of results.

D. *Conflict resolution*

The approach to solve the conflicts in collaborative clustering works in an iterative way. At each iteration, one conflict is selected and its resolution is computed. The resolution of a conflict uses one of the three operators: split, merge and recluster. These operators are used to modify the results. The implementation of these operators depends on the clustering algorithm used. The process iterates, and one conflict is solved at each step if this conflict improves the local agreement (4). If the resolution of this conflict is not relevant, this conflict is removed from the conflict list. When the list of conflicts is empty, the process stops. At the end of the collaboration, the different results are expected to be highly similar. If the user needs a single result, the different similar results can be unified using a voting algorithm or by selecting one result.

III. Sensor simulation

A. *Sensor simulation applications*

Sensor simulation, also called band simulation or band synthesis, consists in generating simulated multispectral spectra from data acquired by existing sensors, with higher spectral resolution. This simulation consists in combining narrow hyperspectral bands into broader multispectral bands. This kind of approach has already been used, especially for sensor calibration and sensor simulation. The spectra simulation step uses the Relative Spectral Response (RSR) functions of the multispectral sensor, which describes the spectral response of each simulated sensor's band. The Figure 1 presents the RSR function of three satellite sensors: Quickbird, SPOT5 and Landsat.

Sensor simulation has already been used for different application. For example, Salvatore et al.[9] used band simulation to simulate the response of a new sensor from AVIRIS data. This simulation allowed the investigators to evaluate in advance the potentialities of the new multispectral sensor. This kind of simulation provides an opportunity to try variations in the original spectral response, and to adjust the RSR to achieve better results for the multispectral sensor objectives. Herold et al.[1] studied spectral resolution requirements for mapping urban areas. They used AVIRIS data and an urban spectral library to study the most suitable spectral bands in separating urban land cover types. The AVIRIS data were also used to simulate Landsat TM and Ikonos data. The results showed that Ikonos and Landsat TM lack of spectral details to efficiently map several urban classes.

B. *Sensor simulation method*

To simulate multispectral data from hyperspectral data, the responses of narrow hyperspectral bands have to be aggregated. However, the reflectance values of the hyperspectral narrow bands cannot be summed directly to reproduce multispectral bands. Indeed, they must be weighted to account for the relative response of the multispectral bands. The RSR of each band of a sensor system is characterized by the effective spectral quantum efficiency, which indicates the spectral sensitivity of the band at each wavelength [10]. Each sensor has consequently a different spectral sensitivity, which is described by its individual RSR functions.

As stated by Clark et al.[11], different strategies have been proposed to compute the weights to apply to each hyperspectral band. For the simulation used in this paper, each hyperspectral center wavelength was linked with the mean RSR value (in the range of the *full width half maximum* (FWHM) of the hyperspectral spectral band) of the simulated band. This approach is similar to the one proposed by Franke et al.[10] and is described in details in [12].

One should notice that in this study some external parameters are not simulated. For example, some other simulation approaches [13] take into account other variables like atmospheric effects or geometric differences between sensors. In this study, we are interested on the sensor discrimination ability according to their RSR, that is why we only focused on spectral differences caused by different RSR functions. However other aspects like the spatial resolution should also be investigated and simulated to truly assess the difference between sensors. However, focusing only on spectral resolution already provides some insight on each sensor capability. The six different sensors were used in this study: Spot5, Quickbird, Pleiades, Landsat TM, Ikonos and Formosat.

IV. Experiment

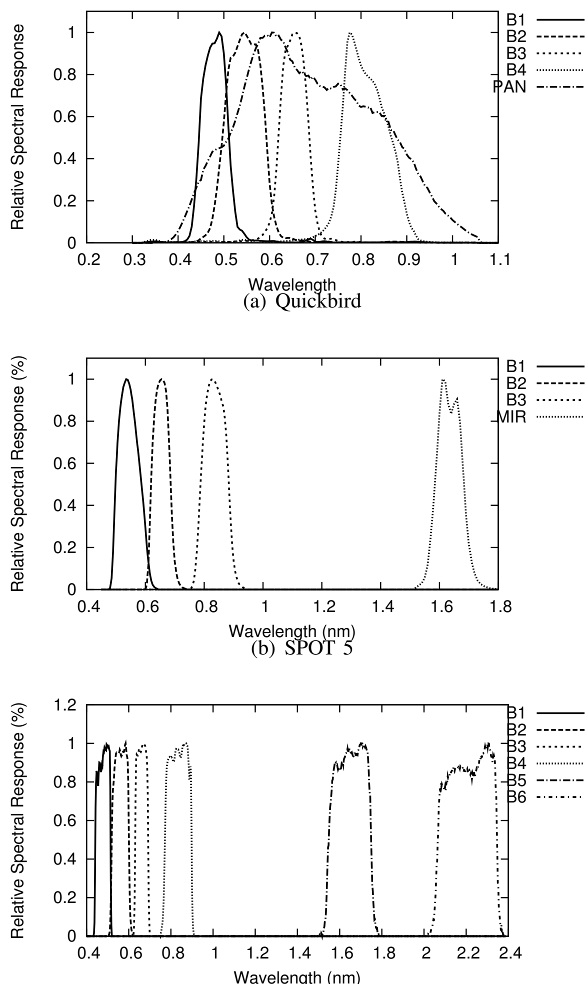
A. *Spectral libraries*

Spectral libraries are repositories of spectra of various kinds of materials (e.g. mineral, man-made material, vegetation...) generally captured *in situ* using field instruments.

Different spectral libraries are freely available. In this study we used the ASTER[14] library which includes contributions from the Jet Propulsion Laboratory (JPL), Johns Hopkins University (JHU) and the United States Geological Survey (USGS). This library contains spectra of rocks, minerals, lunar soils, terrestrial soils, man-made materials, meteorites, vegetation, snow and ice covering the visible through thermal infrared wavelength region (0.4-15.4 μm). The first version was released in July 1998 and the second one is available since 2007 on simple request through the ASTER website[1]. To the best of our knowledge the ASTER library is the most comprehensive and freely available library.

The spectra of this library were convolved with the RSR of each sensor to create different views of the library. Indeed, the simulation process allows us to simulate the sensor view of each library's spectra. Consequently, we have for each spectra of the library its view according to the characteristics of the sensor. This is illustrated with the Figure 3 which presents a full spectrum extracted from the ASTER library, and Figure 2

[1] http://speclib.jpl.nasa.gov



(a) Quickbird

(b) SPOT 5

(c) Landsat

Fig. 1. Example of three *Relative Spectral Response* (RSR).

which presents the simulated spectra for each sensor used in this study. The aim is to use these different views of the same data in order to evaluate the benefit of using various satellite information simultaneously.

B. Evaluation

To evaluate the benefit of using different views of the data, we carried out a series of experiments which consisted in evaluating the interest of the collaboration between couple of satellite systems. Indeed, as remote sensing image acquisition is still expensive, users cannot generally afford to buy more than two images of the same area. Consequently, evaluating the interest of the collaboration of a couple of satellite systems is of particular interest.

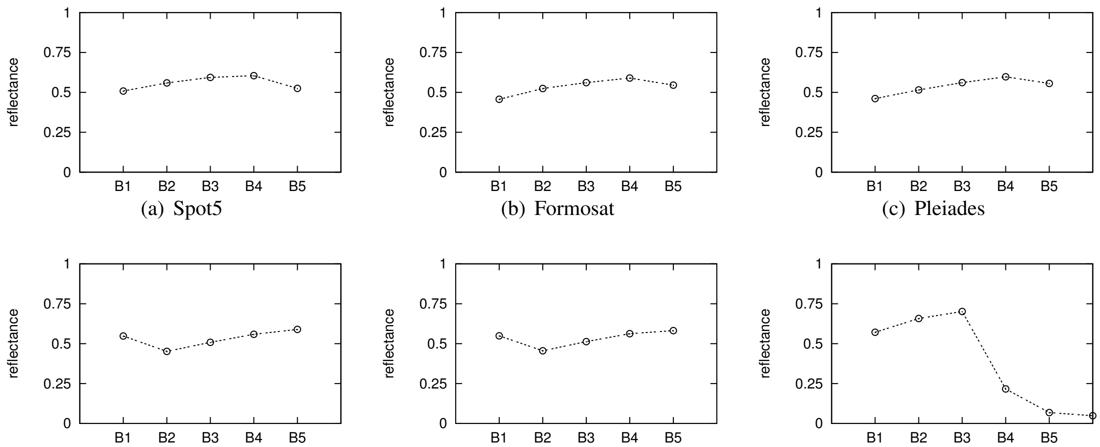
We used the collaborative clustering approach to study if the collaboration between two satellite systems was interesting. For each couple of satellite systems, the collaborative clustering method was used with two clustering methods working on the two different views of the data. In order to evaluate if the use of different data views was interesting instead of using only one view, we also calculated the accuracy for different other configurations. Let D_1 be the data view of the first satellite and D_2 the data view of the second one. The evaluated configurations are:

- D_1 : evaluation of the use of only the first satellite view
- D_2 : evaluation of the use of only the second satellite view
- $D_1 + D_2$: evaluation of the collaboration between the two views by merging the description of the objects from D_1 and from D_2. Each object is then described by the attributes from D_1 and D_2
- $D_1 \circlearrowleft D_1$: collaboration using two times the view of D_1 (two methods using the dataset D_1 as input)
- $D_2 \circlearrowleft D_2$: collaboration using two times the view of D_2 (two methods using the dataset D_2 as input)
- $D_1 \circlearrowleft D_2$: collaboration using two methods using the two views of the data D_1 and D_2

In each of the experiment, we used the KMeans algorithm as base clustering method. For the configuration involving only one dataset (i.e. the first three), the KMeans algorithm was initialized to find a number of cluster equals to the number of classes of the dataset. For the collaboration configuration (the remaining three), each of the KMeans method was initialized randomly with a number of clusters chosen in $[5; 10]$. This choice was made to insure a certain diversity of the two results which is mandatory to obtain an interesting collaboration between the two methods. The clustering results obtained with and without collaboration were evaluated thanks to two well known partition evaluation indexes: the Jaccard (J) index and the Folks-Mallows (FM) index.

Table I presents the results for each configuration (15 pairs of satellite systems). The values in the table are means and standard deviations on 100 runs of each experiment. Note that for the collaboration involving two times the same dataset we only present the results of one of the method as the results at the end of the collaboration were identical. The two columns ($D_1/D_1 \circlearrowleft D_2$) and ($D_2/D_1 \circlearrowleft D_2$) are the results for each method at the end of the collaboration involving the two different views (D_1 and D_2). The last column indicates if the collaboration was beneficial or not (i.e. if the results were better when using the two views). The $\bullet$ sign indicates that the collaboration was beneficial, and the sign $\circ$ that it was not.

The use of the two views in the collaboration was beneficial nine times out of fifteen for the ASTER dataset. The sensor which seems to better leverage from the collaboration is SPOT5 as its results improved for four different collaborations with Pleiades, Landsat, Formosat and Quickbird. The use of data provided by very similar sensors like Pleiades and Quickbird, which have very close RSR, does not seems to be interesting. However, the use of very different sensors like Ikonos and Landsat seems to be beneficial. These results support the idea that it is more interesting to combine very different sensors which can consequently provide different and complementary information. The collaboration using very similar sensors is not relevant as the information are not



(a) Spot5 (b) Formosat (c) Pleiades

(d) Quickbird (e) Ikonos (f) Landsat

Fig. 2. Example of simulated spectra of a spectrum extracted from the ASTER library.

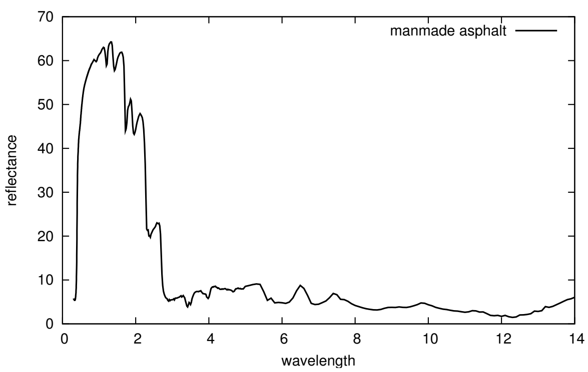


Fig. 3. Example of a full spectrum of a man-made asphalt extracted from the ASTER library.

complementary and rather correlated.

V. Conclusion

In recent years, the availability of satellite data greatly increased. Consequently, a large amount of potential data is now available. The users often use multiple data sources of the same area to better grasp the complexity of the Earth surface. However, as the acquisition of images is still expensive, it is of particular interest to possess simulation tools able to evaluate the interest of using multiple sources of data. In this paper we presented such a tool through collaborative clustering. We presented how the different views of the data can be simulated using spectral library and sensor characteristics (RSR). Six different satellites were simulated, and the collaboration between each couple of satellites was evaluated. We identified several configurations where the collaboration between multisource data was worthy.

However, the simulation approach presented in this paper does not take into account several parameters like the spatial resolution of the sensor (i.e. the size of one pixel) and the atmospheric effects. Further studies have to be carried out to better assess the differences between each sensor. However, the study presented in this paper already provides some insights and can be used as a starting point for further studies.

References

[1] M. Herold, M. Gardner, and D. Roberts, "Spectral resolution requirements for mapping urban areas," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 41, no. 9, pp. 1907–1919, 2003.

[2] D. Meyer and G. Chander, "The effect of variations in relative spectral response on the retrieval of land surface parameters from multiple sources of remotely sensed imagery," *IEEE International Geoscience and Remote Sensing Symposium*, pp. 5150–5153, 2007.

[3] U. Heidena, K. Segl, S. Roessner, and H. Kaufmann, "Determination of robust spectral features for identification of urban surface materials in hyperspectral remote sensing data," *Remote Sensing of Environment*, vol. 111, pp. 537–552, 2007.

[4] M. Govender, K. Chetty, and H. Bulcock, "A review of hyperspectral remote sensing and its application in vegetation and water resource studies," *Water SA*, vol. 33, no. 2, pp. 145–152, 2007.

[5] P. Gancarski and C. Wemmert, "Collaborative multi-step mono-level multi-strategy classification," *Journal on Multimedia Tools and Applications*, vol. 35, no. 1, pp. 1–27, 2007.

[6] G. Forestier, C. Wemmert, and P. Gancarski, "Multi-source images analysis using collaborative clustering," *EURASIP Journal on Advances in Signal Processing - Special issue on Machine Learning in Image Processing*, 2008.

[7] P. Rousseeuw, "Silhouettes: a graphical aid to the interpretation and validation of cluster analysis," *Journal of Computational and Applied Mathematics*, vol. 20, no. 1, pp. 53–65, 1987.

[8] D. Davies and D. Bouldin, "A cluster separation measure," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 4, no. 1, pp. 224–227, 2000.

[9] E. Salvatore, C. Esposito, T. Krug, and R. Green, "Simulation of the spectral bands of the ccd and wfi cameras of the cbers satellite using aviris data," 1999.

[10] J. Franke, V. Heinzel, and G. Menz, "Assessment of ndvi- differences caused by sensor specific relative spectral response functions," *IEEE International Geoscience and Remote Sensing Symposium*, pp. 1138–1141, 2006.

[11] R. Clark, G. A. Swayze, K. Livo, R. F. Kokaly, T. V. V. King, J. B. Dalton, J. S. Vance, B. W. Rockwell, T. Hoefen, and R. R. McDougal, "Synthesis of multispectral bands from hyperspectral data: Validation based on images acquired by aviris, hyperion, ali, and etm+," 2002.

[12] G. Forestier, J. Inglada, C. Wemmert, and P. Gancarski, "Mining spectral libraries to study sensors' discrimination ability," in *SPIE Europe Remote Sensing*, 2009.

TABLE I

EVALUATION OF THE COLLABORATION OF PAIRS OF SATELLITE SYSTEMS.

		D_1	D_2	D_1+D_2	$D_1 \circlearrowleft D_1$	$D_2 \circlearrowleft D_2$	$D_1/D_1 \circlearrowleft D_2$	$D_2/D_1 \circlearrowleft D_2$	
D_1=pleiades	J	0.283 (0.002)	0.283 (0.003)	0.281 (0.001)	0.272 (0.056)	0.295 (0.042)	0.291 (0.094)	0.292 (0.093)	○
D_2=formosat	FM	0.447 (0.002)	0.445 (0.003)	0.444 (0.002)	0.438 (0.059)	0.464 (0.043)	0.460 (0.099)	0.461 (0.098)	○
D_1=pleiades	J	0.282 (0.001)	0.283 (0.001)	0.283 (0.001)	0.214 (0.083)	0.183 (0.018)	0.465 (0.099)	0.465 (0.098)	•
D_2=spot5	FM	0.446 (0.002)	0.448 (0.001)	0.448 (0.001)	0.387 (0.079)	0.365 (0.023)	0.653 (0.111)	0.654 (0.109)	•
D_1=pleiades	J	0.285 (0.004)	0.285 (0.002)	0.283 (0.005)	0.211 (0.033)	0.262 (0.065)	0.311 (0.073)	0.311 (0.077)	•
D_2=ikonos	FM	0.449 (0.004)	0.447 (0.002)	0.445 (0.005)	0.390 (0.030)	0.426 (0.064)	0.484 (0.071)	0.483 (0.076)	•
D_1=pleiades	J	0.284 (0.001)	0.288 (0.001)	0.287 (0.002)	0.258 (0.044)	0.263 (0.060)	0.408 (0.074)	0.406 (0.073)	•
D_2=landsat	FM	0.449 (0.002)	0.454 (0.001)	0.452 (0.002)	0.432 (0.037)	0.445 (0.056)	0.586 (0.085)	0.584 (0.084)	•
D_1=pleiades	J	0.285 (0.002)	0.283 (0.001)	0.284 (0.005)	0.272 (0.085)	0.239 (0.068)	0.236 (0.054)	0.234 (0.055)	○
D_2=quickbird	FM	0.450 (0.002)	0.445 (0.001)	0.446 (0.005)	0.446 (0.082)	0.407 (0.065)	0.397 (0.054)	0.394 (0.056)	○
D_1=formosat	J	0.283 (0.003)	0.286 (0.001)	0.282 (0.002)	0.226 (0.042)	0.208 (0.058)	0.359 (0.015)	0.357 (0.013)	•
D_2=spot5	FM	0.446 (0.003)	0.451 (0.001)	0.446 (0.002)	0.391 (0.044)	0.386 (0.056)	0.531 (0.018)	0.528 (0.016)	•
D_1=formosat	J	0.283 (0.003)	0.283 (0.001)	0.284 (0.000)	0.211 (0.073)	0.224 (0.066)	0.252 (0.048)	0.253 (0.048)	○
D_2=ikonos	FM	0.445 (0.002)	0.445 (0.001)	0.446 (0.000)	0.379 (0.073)	0.397 (0.060)	0.419 (0.047)	0.420 (0.047)	○
D_1=formosat	J	0.281 (0.001)	0.287 (0.001)	0.287 (0.002)	0.298 (0.027)	0.258 (0.032)	0.399 (0.035)	0.391 (0.043)	•
D_2=landsat	FM	0.443 (0.001)	0.453 (0.002)	0.452 (0.003)	0.465 (0.029)	0.443 (0.033)	0.577 (0.041)	0.568 (0.050)	•
D_1=formosat	J	0.283 (0.004)	0.285 (0.003)	0.285 (0.002)	0.215 (0.062)	0.259 (0.064)	0.223 (0.057)	0.226 (0.057)	○
D_2=quickbird	FM	0.445 (0.004)	0.448 (0.003)	0.447 (0.002)	0.387 (0.062)	0.420 (0.066)	0.388 (0.061)	0.392 (0.061)	○
D_1=spot5	J	0.285 (0.001)	0.286 (0.004)	0.282 (0.002)	0.250 (0.044)	0.204 (0.052)	0.422 (0.092)	0.421 (0.093)	•
D_2=ikonos	FM	0.450 (0.001)	0.448 (0.004)	0.446 (0.002)	0.426 (0.045)	0.368 (0.056)	0.603 (0.106)	0.601 (0.107)	•
D_1=spot5	J	0.285 (0.001)	0.288 (0.002)	0.288 (0.001)	0.217 (0.054)	0.246 (0.023)	0.281 (0.093)	0.279 (0.095)	○
D_2=landsat	FM	0.450 (0.002)	0.453 (0.002)	0.453 (0.002)	0.392 (0.055)	0.429 (0.020)	0.455 (0.091)	0.451 (0.094)	○
D_1=spot5	J	0.285 (0.001)	0.287 (0.004)	0.280 (0.001)	0.285 (0.041)	0.192 (0.047)	0.365 (0.042)	0.367 (0.045)	•
D_2=quickbird	FM	0.450 (0.002)	0.449 (0.004)	0.444 (0.002)	0.453 (0.039)	0.360 (0.048)	0.539 (0.047)	0.542 (0.050)	•
D_1=ikonos	J	0.284 (0.003)	0.288 (0.001)	0.288 (0.001)	0.273 (0.068)	0.207 (0.045)	0.366 (0.039)	0.363 (0.043)	•
D_2=landsat	FM	0.446 (0.003)	0.453 (0.002)	0.453 (0.002)	0.444 (0.064)	0.394 (0.049)	0.539 (0.046)	0.535 (0.050)	•
D_1=ikonos	J	0.286 (0.004)	0.284 (0.003)	0.283 (0.001)	0.205 (0.058)	0.196 (0.036)	0.227 (0.081)	0.230 (0.084)	○
D_2=quickbird	FM	0.448 (0.004)	0.446 (0.003)	0.445 (0.001)	0.366 (0.059)	0.358 (0.036)	0.396 (0.080)	0.400 (0.084)	○
D_1=landsat	J	0.289 (0.001)	0.284 (0.001)	0.287 (0.002)	0.271 (0.040)	0.252 (0.037)	0.398 (0.080)	0.399 (0.078)	•
D_2=quickbird	FM	0.455 (0.001)	0.446 (0.002)	0.452 (0.003)	0.459 (0.042)	0.422 (0.033)	0.575 (0.093)	0.576 (0.090)	•

[13] K. T., "Simulating landsat etm+ imagery using dais 7915 hyperspectral scanner data," *International journal of remote sensing*, vol. 25, no. 22, pp. 5049–5067, 2004.

[14] A. M. Baldridge, S. J. Hook, C. I. Grove, and R. g., "The aster spectral library version 2.0," *Remote Sensing of Environment*, 2008.