EVALUATING THE POTENTIAL OF TEXTURE AND COLOR DESCRIPTORS FOR REMOTE SENSING IMAGE RETRIEVAL AND CLASSIFICATION

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Abstract: Classifying Remote Sensing Images (RSI) is a hard task. There are automatic approaches whose results normally need to be revised. The identification and polygon extraction tasks usually rely on applying classification strategies that exploit visual aspects related to spectral and texture patterns identified in RSI regions. There are a lot of image descriptors proposed in the literature for content-based image retrieval purposes that may be useful for RSI classification. This paper presents a comparative study to evaluate the potential of using successful color and texture image descriptors for remote sensing retrieval and classification. Seven descriptors that encode texture information and twelve color descriptors that can be used to encode spectral information were selected. We perform experiments to evaluate the effectiveness of these descriptors, considering image retrieval and classification tasks. To evaluate descriptors in classification tasks, we also propose a methodology based on KNN classifier. Experiments demonstrate that Joint Auto-Correlogram (JAC), Color Bitmap, Invariant Steerable Pyramid Decomposition (SID) and Quantized Compound Change Histogram (QCCH) yield the best results.

1 INTRODUCTION

Agriculture has an important role in the economy of several countries. The results of agricultural activities are directly linked to the productivity. Therefore, many researches have been investigating new ways to improve agricultural practices and, consequently, to increase the quantity and quality of what is produced. In this scenario, crop monitoring is a fundamental activity and using Geographic Information Systems (GIS) has made it easier.

Some of the main issues related to crop monitoring are: How is the land occupation? What is cultivated in a given region? Where are some cultures cultivated?

Remote Sensing Images (RSIs) provide the basis for the creation of information systems that support the decision-making process based on land cover changes. Using RSI in crop monitoring requires the recognition of the regions of interest and the extraction of the polygons around these regions.

The identification and polygon extraction tasks usually rely on applying classification strategies that exploit visual aspects related to spectral and texture patterns identified in RSI regions. These tasks can be performed automatically or manually. The "manual" approach is based on image editors by witch users can define or draw polygons that represent regions of interest using the raster image as background. In general, automatic approaches use classification strategies based on pixel information. However, the most used pixel classification algorithm, MaxVer (Showengerdt, 1983) is not always effective.

The main drawback of automatic approaches is concerned with its sensitivity to image noises (e.g., for example, distortions that can be found in mountainous regions). Another important problem in the automatic approaches is concerned with the fact that they usually fail to correctly identify borders between distinct regions within the same image. Thus, in practical situations, the results obtained need to be revised. As these revisions take a lot of time, it is sometimes more convenient to the user to perform recognition manually.

Content-based Image Retrieval (CBIR) systems are developed to provide efficient and effective means to retrieve images. In these systems, the searching process consists of, for a given image, computing the most similar images stored in the database, considering only image properties, like color and texture, for

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instance. The searching process relies on the use of image *descriptors*. A descriptor can be characterized by two functions: *feature vector extraction* and *similarity computation*. The similarity between two images is computed as a function of their feature vectors distance.

This paper presents an evaluation of image descriptors for RSI retrieval and classification. Seven descriptors that encode texture information and twelve color descriptors that can be used to encode spectral information were selected. We perform experiments to evaluate the effectiveness of these descriptors in retrieval sessions and classification tasks.

2 RELATED WORK

Several methods have been proposed to improve the performance of RSI classification techniques. In (Mo et al., 2007), a new method considering image segmentation, GIS, and data mining algorithms was presented. Compared with pixel-based classification, the results showed best agreement with visual interpretation. The work proposed in (Yildirim et al., 2005) applied a morphological filter in an image which was classified by MaxVer algorithm. The results were compared with the other classification algorithms (Fisher linear likelihood, minimum Euclidean distance and ECHO). In (hyung Kim et al., 2007), three Land Cover Classification Algorithms are compared for monitoring North Korea using multi-temporal data.
Recently, some descriptors for RSI purposes have been proposed. Tusk et. al. (Tusk et al., 2003) presented algorithms that allow automatic selection of features for region and tile similarity searches applying relevance feedback. Samal et. al. (Samal et al., 2009) proposed a RSI descriptor, called SIMR (Satellite Image Matching and Retrieval). SIMR computes spectral and spatial attributes of the images using a hierarchical representation. A unique aspect of this descriptor are the couples of second-level spatial autocorrelation with quad tree structure.

There is a large number of image descriptors proposed in the literature for CBIR that can be useful to classify and recognize RSI regions. Using descriptors, systems can compute how similar regions of an image are when compared to a spectral or texture pattern in which users are interested. This information can, therefore, be used to classify the whole image. Santos et. al. (dos Santos et al., 2009) presented a semi-automatic method to vectorize regions from remote sensing images using relevance feedback based on genetic programming (GP). The solution consists of using image descriptors to encode texture and spectral features from the images, applying relevance feedback based on GP to combine these features with information obtained from the users interactions and, finally, segment the image. At the end, segmented image (raster) is converted into a vector representation.

Descriptors effectiveness can vary from one application to another. This fact shows the importance of evaluating descriptors considering specific applications. A comparative study of color descriptors for Web image retrieval is presented in (Penatti and Torres, 2008). However, to the best of our knowledge no study has been conducted to evaluate the performance and effectiveness of image descriptors in RSI retrieval and classification tasks.

3 IMAGE DESCRIPTORS

The descriptors chosen for the evaluation are important descriptors from the literature and recently proposed descriptors.

The color descriptors evaluated in this work are: GCH (Swain and Ballard, 1991), CGCH (Stricker and Orengo, 1995), LCH (Swain and Ballard, 1991), CCV (Pass et al., 1996), ACC (Huang et al., 1997), JAC (Williams and Yoon, 2007), BIC (de O. Stehling et al., 2002), CBC (de O. Stehling et al., 2001), Color Bitmap (Lu and Chang, 2007), CSD (Manjunath et al., 2001), CW-HSV (Utenpattanant et al., 2006) and CM (Paschos et al., 2003).
The texture descriptors evaluated in this work are: LBP (Ojala et al., 2002), HTD (Wu et al., 2000), SID (Zegarra et al., 2007), CCOM (Kovalev and Volmer, 1998), Unser (Unser, 1986), QCCH (Huang and Liu, 2007), and LAS (Tao and Dickinson, 2000).

4 EXPERIMENTS

This section presents the databases used in the experiments and the measures used to evaluate the descriptors.

4.1 Image Databases

Two image databases were created to evaluate image descriptors based on distinct RSIs. One of them can be classified as “easy recognition” (pasture image) while the other as “hard recognition” (coffee image). Information about the used RSIs is showed in Table 1.

In the experiments, one image is represented by a tile from the original RSI. The size of the tile was

Table 1: Remote Sensing Images used in the experiments.

	Image1	**Image2**
Region of interest	pasture	coffee
Terrain	plain	mountainous
Satelite	CBERS	SPOT
Spatial resolution	20 meters	2,5 meters
Bands composition	R-IR-G (342)	IR-NIR-R (342)
Acquisition date	08–20–2005	08–29–2005
Location	Laranja Azeda Basin, MS	Monte Santo County, MG
Dimensions (px)	1310×1842	2400×2400

fixed according to the common extension value of a *region of interest*. Coffee crops are normally in small parcels on the same farm. We defined that 75×75 *meters* is a good value to the size of the partition. For pasture parcels, that are larger, the chosen value was 400×400 *meters*. The dimension of partitions are fixed in the experiments. We used 30×30 *pixels* to partition the coffee image and 20×20 *pixels* for the pasture image. The number of partitions for the pasture and coffee images was 5980 and 6400, respectively.

A "mask" containing all regions of interest from the RSIs used in the experiments was used to know the class of each tile. A "mask" is a binary image where value 1 represents pixels of regions of interest. The "masks" used in our experiments were classified manually by agricultural specialists.

4.2 Evaluation Measures

The main objective of the experiments was to evaluate and compare the descriptors considering effectiveness issues. For this purpose, we configured two experiments: retrieval effectiveness evaluation and overall accuracy classification.

To evaluate retrieval effectiveness, Precision $\times$ Recall curves were used. *Precision* quantifies the percentage of relevant images present in the retrieved results. *Recall* is a measure that represents the percentage of the relevant images that are retrieved. A Precision $\times$ Recall curve indicates the variation in Precision values as the rate of relevant images from the database (Recall) changes. Intuitively, the higher the curve, the better the effectiveness. The Precision and Recall curves were computed based on the average values obtained for each query image in each database. We used 340 and 100 queries in the Pasture and Coffee image sets respectively for all the color and texture descriptors presented in Section 3.

To compute the overall accuracy of each descriptor we implemented a variation of K-Nearest Neighboor (KNN) classifier. First of all, a set of tiles from the database was randomly selected to be used as training set. The set, corresponding to 10% of the database size, is composed by relevants and non-relevants samples in the same proportion found in the full database. To classify one tile, each descriptor evaluated was used to compute the distance between the given tile and all the training set tiles. Based on the descriptor distances, the training set is ranked and the first K tiles are weighted inversely proportional to their position in the rank. Finally, the sum of the tiles' weights for each class (relevant or non-relevant) is computed. The greater sum indicates the class of the input tile. To test the classification effectiveness of the descriptors 100 tiles were used for each RSI.

4.3 Results

Figures 1, 2, 3, and 4 show the Precision $\times$ Recall curves for color and texture descriptors in the databases used.

From Figure 1 we can see that good descriptors considering retrieval effectiveness are JAC, Color Bitmap, and ACC.

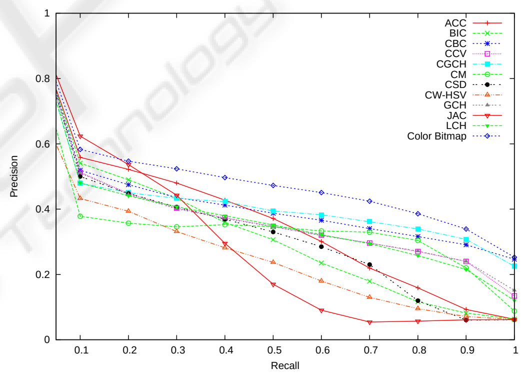

Figure 1: Precision $\times$ Recall curves for color descriptors in the Pasture Image Set.

From Figure 2, it is possible to see that JAC presents the highest Precision values even for small values of Recall and for Recall equal to 1.

Analyzing Figure 3 it is possible to notice that SID has the highest Precision values for all values of Recall.

Considering curves for the Coffee database in Figure 4, it is possible to see that the descriptors present very similar Precision values and these values are near 32% when Recall reaches 10%.

After analyzing the curves for color and texture descriptors it is possible to say that color descriptors are slightly better than texture descriptors for the databases used. For example, in the Pasture database, for Recall equal to 10%, the highest Precision value for color descriptors is around 62% (JAC) and for

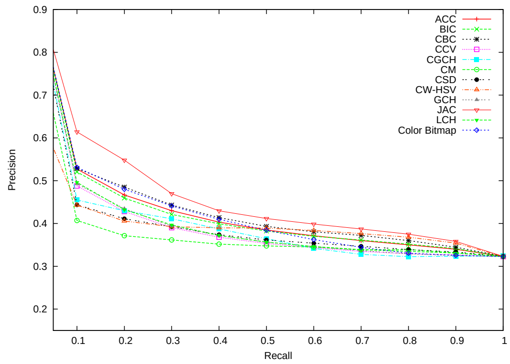

Figure 2: Precision × Recall curves for color descriptors in the Coffee Image Set.

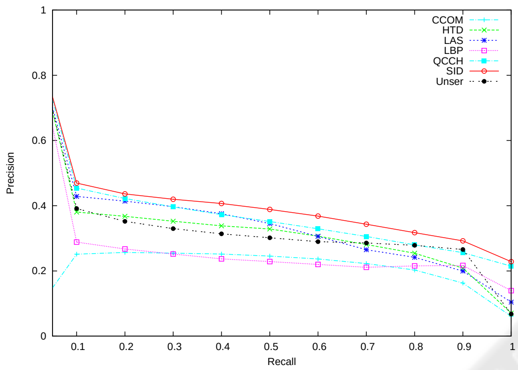

Figure 3: Precision × Recall curves for texture descriptors in the Pasture Image Set.

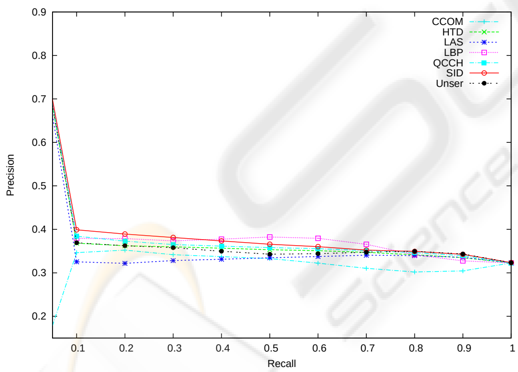

Figure 4: Precision × Recall curves for texture descriptors in the Coffee Image Set.

texture descriptors is near 47%. For Recall equal to 1, color descriptors achieve Precision of 25% (Color Bitmap) and texture descriptors achieve almost 23% . For the Coffee database, it is possible to notice that, for Recall equal to 10%, the highest curve of a color descriptor reaches 61% (JAC) while the highest curve of a texture descriptor reaches almost 40% (SID). For Recall equal to 1, there is almost no difference in the Precision values.

According to the results for the coffee database presented (Figure 5), is observed that some descriptors achieved high overall accuracy values. The color descriptors BIC, ACC, CBC, Color Bitmap, and JAC were the best ones reaching more than 60% of overall accuracy for any k. JAC produced the highest accuracy values, being the only one with values over 70% (72% for k=1, 79% for k=3, and 73% for k=7 and k=10). With regard to the texture descriptors, QCCH, SID, and LAS yielded the highest accuracy values, 52% for k=3. For k values different than 3, the texture descriptors presented accuracy below 48%. The CCOM descriptor did not reach 25% of accuracy in any of the experiments in the coffee database.

According to the results for the pasture database presented (Figure 6) we can see that some descriptors yielded good accuracy values. The color descriptors JAC, Color Bitmap, and CBC reached near or more than 60% of overall accuracy. JAC descriptor was again the descriptor with highest accuracy value, reaching 78% for k=3 and being over 65% for all k values. The texture descriptors yielded lower accuracy values when compared with most of color descriptors. QCCH, SID and Unser were the only texture descriptors to reach accuracy above 50%. For k=3, QCCH reached 58% of accuracy, SID 55% and Unser 53%. CCOM descriptor reached the lowest accuracy values, being below 25% for all k values.

Considering the accuracy values in both image databases, we can point JAC as the best color descriptor. However, JAC generates big feature vectors and so, it is slower to compare them. If storage and time requirements are not critical, JAC is the best choice. Other descriptors with near effectiveness are CBC and Color Bitmap. CBC has complex extraction and distance function. Color Bitmap is the best choice among the color descriptors, which balance simple algorithms and good effectiveness. Amongst the texture descriptors, QCCH and SID reached the highest accuracy values, being SID computationally more complex than QCCH for features extraction.

5 CONCLUSIONS

This paper presents a comparative study of image descriptors for the classification and recognition of RSI regions. Twelve color descriptors and seven texture descriptors were compared considering effectiveness issues. The effectiveness was measured by precision-recall curves and overal accuracy. JAC and Color Bitmap presented the best results among the color descriptors evaluated, while SID was the best texture descriptor. We also proposed methodology to evaluate

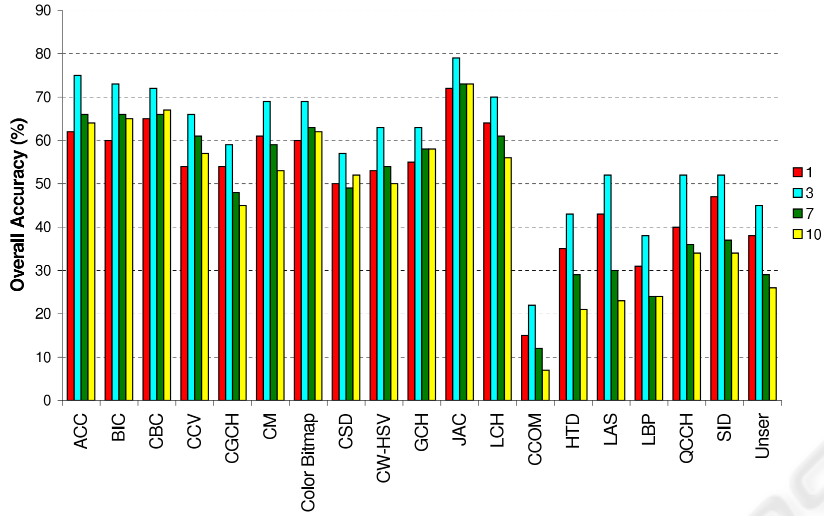

Figure 5: Overall accuracy classification of each descriptor for Coffee using KNN 1, 3, 7 and 10.

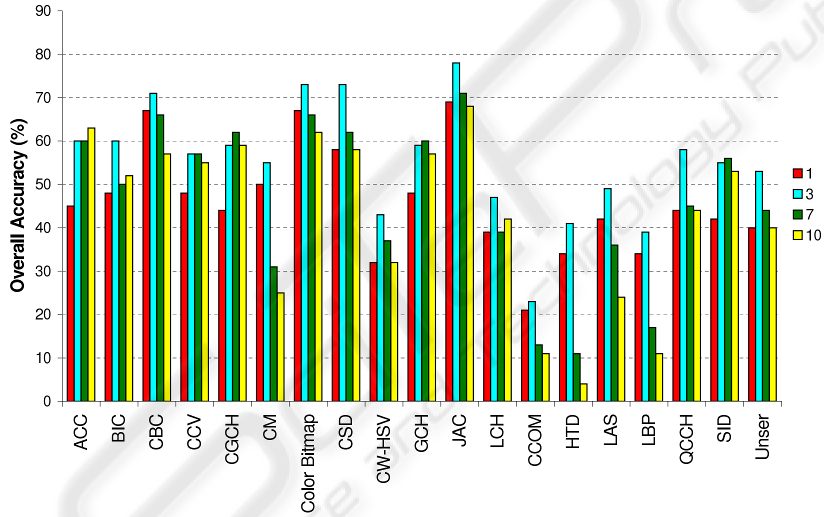

Figure 6: Overall accuracy classification of each descriptor for Pasture KNN 1, 3, 7 and 10.

image descriptors in classification problems by using KNN classifier.

The next stage of this work is to combine the best descriptors and to evaluate their use in RSI classification tasks.

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