Automatic color indexing of hierarchically structured classified images

André R. S. Marçal
Faculdade de Ciências
Universidade do Porto
Porto, Portugal
andre.marcal@fc.up.pt

***Abstract* — The hierarchical structuring of a classified image with N classes provides a set of solutions for a classification problem, with N, N-1, …, 2 classes. The visual analysis of this set of images requires that a consistent color indexing is available for the whole structure. This paper addresses this issue, proposing a number of methods for the automatic assignment of lookup tables for the classified images at the various levels of a hierarchical structure. The various strategies are compared and some methods illustrated with a section of a Landsat TM image classified in 15 classes.**

Color indexing; unsupervised classification; hierarchical clustering; HSI color space

I. INTRODUCTION

Multi-spectral satellite images are often used to produce thematic maps by means of image classification. Supervised classification methods are the most commonly used. These methods require a prior identification of training areas, which are used to characterize the spectral signature of each class. The results from supervised classification are frequently disappointing, both due to the presence of mixed pixels and to the lack of knowledge of the actual classes present in the dataset. Classes that are not spectrally distinguishable might be looked for, and others that have a clear signature in the feature space might not have been initially predicted. These problems are partially removed using unsupervised classification methods, which can be used to reveal structures and to identify "natural" groupings in the feature space. However, the process of a posteriori labeling of the classes assigned to clusters tends to be difficult, particularly because the number of classes (N) produced by the unsupervised classifier is usually high. One strategy used to assist in the process of labeling the classes is to create a hierarchical structure for the N classes. This allows the user to start labeling large groups of pixels, which are then sub-divided into more detailed set of classes. The hierarchical structure can be used to produce N-1 classified images (with N, N-1, …, 2 classes). A consistent system of visualization is required for the entire set of classified images, so that the user can have a good multi-level perception.

This paper presents methodologies for the automatic color indexing of a set of classified images from a hierarchical structure, assuring consistency between the various levels, from the visual perception point of view.

This work was done with the support of "Centro de Investigação em Ciências Geo-Espaciais, Faculdade de Ciências da Universidade do Porto", finaced by "Fundação de Ciência e Tecnologia" through POCTI/FEDER.

II. HIERARCHICAL STRUCTURING CLASSIFIED IMAGES

Hierarchical clustering techniques proceed by either a series of successive mergers or a series of successive divisions [1]. Agglomerative hierarchical methods start with individual objects, or pixels on a digital image. This is a major limitation, as usually satellite images are too big for such a method to be computationally viable on a pixel by pixel basis. An alternative way is to use the agglomerative hierarchical method after the application of some other clustering method. For example, the Isodata method [2] can be used to classify the image into a reasonably small number of classes. The resulting classes from this initial classification are then clustered hierarchically, providing a dendogram that will allow for various levels of discrimination to be extracted from the image data.

An example of a dendogram is presented in Fig. 1, for an image initially with 6 classes. In this case a total of five classified images are produced: the original image with 6 classes, and images with 5, 4, 3 and 2 classes. Moving upwards in the structure concists of finding the two most similar classes, acording to a pre-defined criteria. This can be a distance metric, such as the Euclidean [3] or the Mahalanobis distance [4], or a mixed spectral and spatial criteria [5]. The pixels of the two classes merged together are assigned a new label. For example, in the dendogram of Fig. 1, moving upwards from the lowest level will consist of creating a new image where all pixels belonging to classes 1 and 2 in the original image are assigned the value 7, and the values of all the other pixels are unchanged. Moving from this level to to the next is done by replacing all pixels with values 3 and 7 by the new class value 8. The process is repeated until an image with only two classes is obtained.

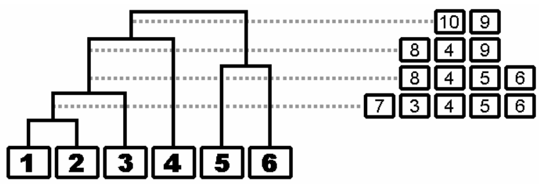

Figure 1. Example of a dendogram, representing the hierarchical structure of an image initially classified in 6 classes.

The labeling process consists of replacing the labels of the two classes merged by a new label. Although this is not a standard practice in hierarchical clustering, it is an important detail for the process of automatic creating lookup tables for the whole set of classified images.

III. Color Indexing

In order to have a good visual perception of the classified images suitable lookup color tables are required. The N classes of an image are assigned to N shades of gray or to N different color. The choice of a lookup color table should take into account two factors: (i) a good visual discrimination between classes, (ii) a clear perception of the relative order of the classes. The visual discrimination between classes is best achieved with color lookup tables, but the correct perception of the relative order of classes is best achieved for gray level lookup tables.

A. Initial color indexing

A simple choice of a lookup color table for a classified image is to use the whole range of gray levels. The N classes are equally spread through the range of gray levels available (L), providing a gray level (G_i) for each class (i)

$$G_i = L*(i-1)/(N-1). \tag{1}$$

The grayscale lookup tables produced by (1) for N=5, 8, 15 and 20 is presented in Fig. 2. The perception of the relative order of classes is very good, but the visual discrimination between classes is somehow difficult for large values of N (e.g. N=20). This could be slightly improved using a nonlinear relation in (1), as the human perception of gray shades is not uniform. However, the use of grayscale lookup tables for classified images is in any case limited, in terms of visual discrimination, to a few tens of classes.

The use of color lookup tables can greatly improve the visual discrimination but give rise to the problem of keeping an adequate perception of the relative order of classes. This issue can be addressed in the Hue Saturation Intensity (HSI) color model [6]. The range of hues (0-360º) is equally spread through the N classes, in a similar way as for gray scale levels (1). However, as the range of hues is closed scale (Min. Hue, 0º = Max. Hue, 360º) it should be divided in N instead of N-1 parts. The Hue assigned to a class (H_i) is obtained by (2), where L_H is a scaling factor

$$H_i = L_H*360*(i-1)/N. \tag{2a}$$

The values of saturation and intensity could also be equally spread for the N classes. However, the ability to visually discriminate between colors with low values of saturation is greatly reduced. The same happens for extreme intensity values, both high and low. The range values used was limited to 60% for the Saturation and to 40% for the Intensity. For each class (i), the Saturation (S_i) is given by (2b) and the Intensity (I_i) by (2c).

$$S_i = L*[1.0–0.4*(i-1)/N] \tag{2b}$$

$$I_i = L*[0.8–0.4*(i-1)/N]. \tag{2c}$$

The HSI values assigned by (2) are converted to the RGB color space and a color lookup table established. The color tables produced for 5, 8, 10 and 20 classes are presented in Fig.2. Comparing to the grayscale versions, the color scales provide better visual discrimination between classes but the relative order of the classes is not so evident.

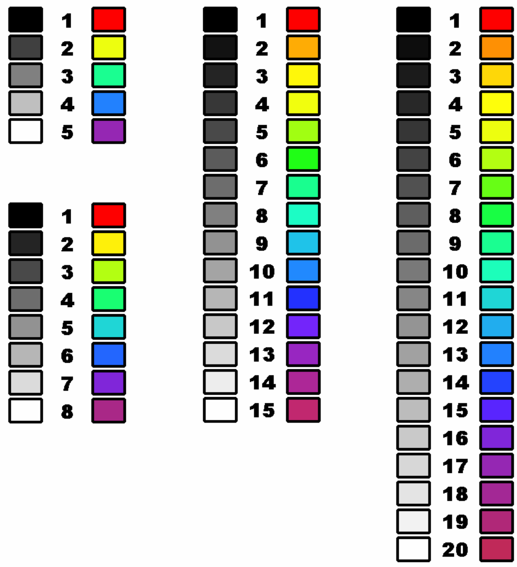

Figure 2. Greyscale and color lookup tables for 5, 8, 15 and 20 classes.

The lookup tables produced by (1) and by (2) are only based on the number of classes (N). An alternative method for the creation of a lookup table is to use the spectral signature of the classes. For color lookup tables, 3 bands of the multi-spectral image are selected and assigned to Red, Green and Blue. The average level in each of the 3 bands is used to obtain a RGB value for each class.

B. Strategies to progress upwards

The methods proposed in the previous section produce a lookup table for a single classified image, but the aim is to have one or several lookup tables for the N-1 classified images in the hierarchical structure. Once a lookup color table is established for the image at the lowest level of the hierarchical structure, a methodology to progress upwards in the dendogram needs to be put in place. Three strategies can be used: (I) an independent assignment for each hierarchical level, (II) new color assignment for a new class, (III) color aggregation. These strategies are illustrated in Fig. 3. In this example, the initial classification produced 6 classes that were hierarchically structured according to the dendogram of Fig. 3. For example, the second hierarchical level has five classes: class 7 (resulting from the merger of classes 1 and 2), and classes 3 to 6.

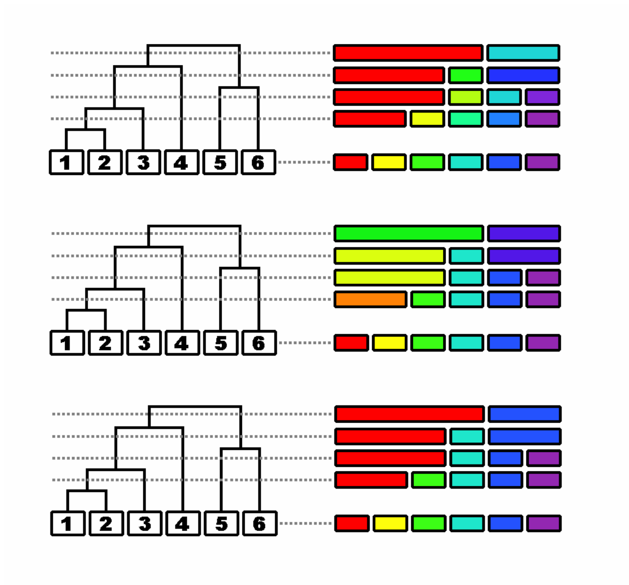

Figure 3. Illustration of three strategies to create pseudocolor tables for hierarchically structured classified images: independent assignement (top), new color for new class (centre), color aggregation (bottom).

The first method is the independent assignment of a color table for each hierarchical level, as illustrated in the top section of Fig. 3. A new color table is assigned for each level in the hierarchical structure, which only depends on the number of classes (N=6, 5, 4, 3, 2). This method, although simple to implement, has two important drawbacks. The first is that it is not possible to produce a single lookup table for the whole set of classified images, as the same class is assigned to different colors in different hierarchical levels. The second problem is the lack of consistency in color assignment between the classified images at different levels.

The second method, illustrated in the central section of Fig. 3, is the assignment of a new color to a new class. The movement upwards in the hierarchical structure is done by merging 2 classes into a new class. The color assigned to this class is the average between the colors of the classes merged. For example, when classes 1 (red, H=0º, S=1.000, I=0.800) and 2 (yellow, H=60º, S=0.934, I=0.734) are merged, the new class 7 is assigned a new color – orange (H=30º, S=0.967, I=0.767). This methods permits that a single lookup table is used for the whole set of classified images, and provides satisfactory results in terms of visual consistency between the various levels.

The color aggregation method is illustrated in the bottom section of Fig. 3. In this method, the new class obtained by the movement upwards in the hierarchical structure will get the color of the biggest (largest number of pixels) of the two classes merged. In the example of Fig. 3, it was considered that class 1 was the biggest, followed by class 2, which is followed by class 3 and so forth. The implementation of this method is done by a single lookup table for the whole set of classified images. It also provides consistent results between the different levels in the hierarchical structure.

IV. RESULTS

A section of a Landsat TM image was selected to illustrate the method. The image section, of 512 by 512 pixels, covers an agricultural area in Northeast Portugal. The image was classified using the Isodata method [2] implemented with the PCI Geomatics software [7]. The 30 classes produced were structured hierarchically using the Euclidian distance metric. To simplify the presentation and analysis, only the upper part of the structure is considered here. The starting point is therefore a classified image with 15 classes. The number of pixels assigned to each class is displayed in Table I.

TABLE I. SUMMARY OF THE TEST IMAGE CLASSIFICATION RESULTS

class		**Mean value**			**Color (8 bits)**		
i	***No. Pixels***	***TM5***	***TM4***	***TM3***	***R***	***G***	***B***
1	109209	68.83	97.96	23.31	19	136	5
2	4825	85.86	121.5	26.62	62	212	20
3	18260	99.17	77.46	41.51	96	70	88
4	5306	108.0	96.95	36.61	119	133	66
5	16108	86.76	94.64	33.09	64	125	50
6	38758	79.28	74.81	31.76	45	61	44
7	22901	83.55	55.74	40.80	56	0	85
8	12883	61.49	134.8	22.12	0	255	0
9	675	127.2	83.82	75.80	168	91	244
10	920	161.4	87.65	78.12	255	103	255
11	11909	121.0	82.60	47.00	152	87	113
12	2943	112.1	72.15	57.81	129	53	163
13	7945	127.8	61.24	43.16	169	18	96
14	6866	138.8	78.44	63.00	197	73	186
15	2421	143.9	68.84	51.00	210	42	132

A lookup color table was produced using (2) for N=15. The color aggregation method was used to extend the initial set of colors to the whole hierarchical structure. The color assignment at each level of the dendogram is presented in Fig. 4.

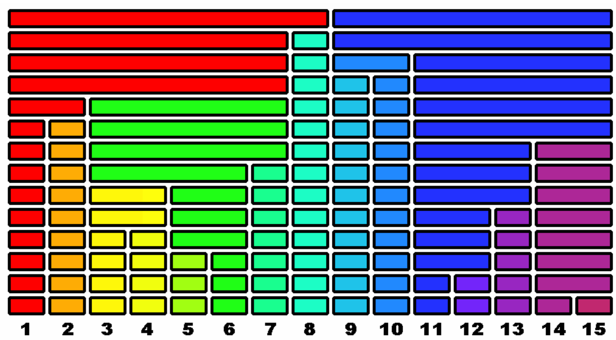

Figure 4. Color assignment for the hierarchical structure of the test image.

An alternative lookup color table was produced for the same dataset. The initial colors assigned to each class were obtained from the RGB color composite of Landsat TM bands 543. The average values for each class in bands 5, 4 and 3 are presented in Table I. As the range of values is very narrow, a linear stretch was performed. The RGB components were converted to HSI color space. The Intensity was linearly starched, and the resulting HSI values converted back to the RGB color space. The RGB colors assigned to each class are presented in 8-bit format in Table I. The progress upwards in the structure was done assigning a new color for each new class. The new color is obtained from the colors of the two classes being merged, by averaging their HSI components. The hierarchical structure with the color assignments for each level is presented in Fig. 5.

The consistency of the classification results in the hierarchical structure can be visually inspected interactively, or by a moving sequence or animation. This is aided by the fact that the whole set of color indexed images share a common lookup table. Fig. 6 shows the test image classified at four levels of the hierarchical structure – 15, 8, 4 and 2 classes – using the color indexing of Fig. 5.

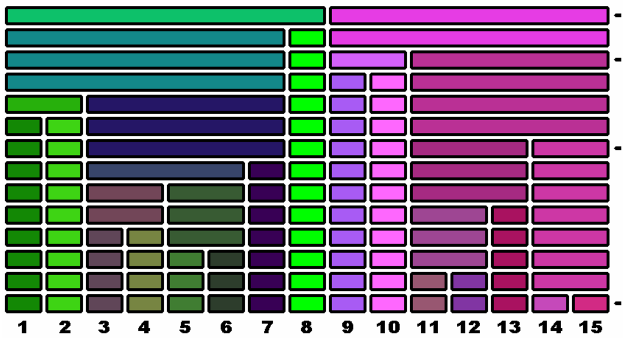

Figure 5. Color assignment for the test image hierarchical structure, with the initial colors obtained from a RGB color composite (TM bands 543).

V. CONCLUSIONS

The application of unsupervised classification algorithms to multi-spectral satellite images usually produces classified images with a large number of classes (N). The a posteriori labeling is greatly assisted by a hierarchical structure of these classes. The structure consists of a set of N-1solutions for a classification problem. The visual inspection of this dataset is greatly benefited by an adequate choice of color indexing for the classified images. The choice of a lookup color table should take into account a good visual discrimination between classes, and a clear perception of the relative order of the classes. The visual discrimination between classes is best achieved with color lookup tables, but the correct perception of the relative order of classes is best achieved for gray level lookup tables.

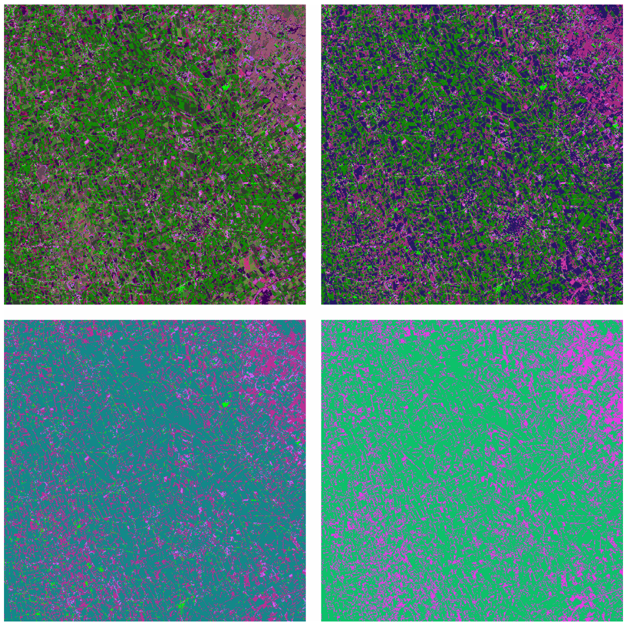

Figure 6. Pseudocolor images of the hierarchical structure with 15 (top left), 8 (top right), 4 (bottom left) and 2 classes (bottom right).

The lookup table for the image at the lowest level of the hierarchical structure can be established based on the number of classes only, or using a RGB composition from the multi-spectral image. Three strategies are described to progress upwards in the hierarchy, two of which are effective in terms of visual consistency for the different levels of the hierarchy. These methods – new color assignment for a new class, color aggregation – allow for a single lookup table to be used for the whole set of classified images. The set of images can be used to produce interactive animations that are useful for image exploration purposes.

REFERENCES

[1] R. A. Johnson and D. W. Wichern, Applied Multivariate Statistical Analysis, Fourth Edition, Prentice Hall, 1998.

[2] J. T. Tou and R.C. Gonzalez, Pattern Recognition Principles, Addison-Wesley, 1974.

[3] J.A. Richards and X. Jia, Remote Sensing Digital Image Analysis, 3rd ed., Berlin, Germany, Springer-Verlag, 1999.

[4] R. O. Duda, P. E. Hart and D. G. Stork, Pattern Classification, Second Edition, John Wiley & Sons, 2001.

[5] André R. S. Marçal and Luísa Castro, 2005 “Hierarchical clustering of multi-spectral images using combined spectral and spatial criteria”, IEEE Geoscience and Remote Sensing Letters, 2, pp. 58-62.

[6] R. C. Gonzalez and R. E. Woods, Digital Image Processing, Second Edition, Prentice Hall, 2003.

[7] PCI GEOMATICS, X-Pace Reference Manual, Version 8.2, PCI Geomatics, Ontario, Canada, 2001.