

# Spectral Image Retrieval using Munsell Data and Unsupervised Classification Methods

*Oili Kohonen and Markku Hauta-Kasari*

*Department of Computer Science and Statistics,*

*P. O. Box 111, FIN-80101 University of Joensuu, Finland*

## **Abstract**

*Color feature based retrieval from a spectral image database by using Self-Organizing Map, K-means clustering and Randomized Local Search algorithms is performed. Furthermore, the usability of 1269 reflectance spectra of the color chips of the Munsell Book of Color Matte Finish Collection as a training data for these algorithms to reduce the time complexity, caused by the massive training data collected from a database to be retrieved, is studied. The retrieval experiments are performed by using a real spectral image database.*

## **Introduction**

An increase in the number of available digital images and image databases has created a need for content-based image retrieval in which the images are represented by their visual content. The most straightforward visual feature is color, color histogram being the most often used color feature. A color histogram representing a spectral image can be constructed by classifying the images spectra into classes generated by unsupervised classification algorithms, and by constructing a normalized histogram over these classes.

In the case of spectral databases, the training data for these algorithms can be generated by collecting a certain number of spectra from a database. However, to achieve a training data versatile enough, one should be able to choose the sufficient amount of spectra from each spectral image in a database. The more

comprehensive is the training data, the more time-consuming is a generation of classes. Moreover, in the case of large databases the number of spectra chosen from each image must be strongly restricted due to the aspects of memory consumption. Besides, if the number of spectra chosen from an image is very small compared to the total number of spectra in the image the effect of randomness will be emphasized.

A method for construction of representative spectra from a large database of spectral reflectance (SOCS) [1] was proposed by Borer and Susstrunk [2]. The database is a commercial product which presumably reduces the use of it. Contrary, Munsell data collection is a commonly used spectral database which covers the CIEL\*a\*b\* color space well and tries to sample color space in a way which reflects the properties of human color perception. Due to these properties and the availability of the data, we examine the possibility to use Munsell data as a training data instead of the data collected from a spectral image database.

The previous studies in the field of spectral image retrieval [3] have been based on the use of Self-Organizing Map algorithm [4]. However, the clustering algorithms which minimize the partition cost should theoretically be able to perform the better partitioning for the spectral space. Therefore, in addition to SOM, we use K-means clustering [5] and Randomized Local Search (RLS) [6] algorithms for generating the classes for spectra.

## Methods for unsupervised classification

Self-Organizing Map (SOM) [4] is a neural network algorithm which defines a topology preserving mapping from a high-dimensional data space into a lower-dimensional space. SOM consists of arranged units which are represented by weight vectors and are connected to adjacent units by a neighborhood relation. At the beginning of the algorithm the weight vectors are initialized and furthermore trained iteratively as presented in Algorithm 1.

### Algorithm 1

```

begin
  Initialize the weight vectors for SOM
  for i = 1 : number of training steps,
    Take vector x randomly from the training data
    Find the Best-Matching Unit for x
    Update weight vectors
    Decrease the learning rate
    Decrease the neighborhood
  end;
end

```

The Best-Matching Unit (BMU) is defined as a unit which produces the smallest distance for an input data vector  $x$  in respect to a chosen distance measure. The commonly used distance measure and neighborhood function are Euclidean distance and Gaussian function. The weight vectors  $W$  are updated using the following Equation

$$w_i(t+1) = \begin{cases} w_i(t) + \beta(t), & i \in N_{BMU}(t) \\ w_i(t), & otherwise \end{cases} \quad (1)$$

in which  $t$  denotes the time,  $N_{BMU}(t)$  is a decreasing neighborhood around the BMU and  $\beta(t)$  is furthermore defined as

$$\beta(t) = \alpha(t)[x(t) - w_i(t)] \quad (2)$$

in which  $x(t)$  is the input data vector and  $\alpha(t)$  is a decreasing learning rate.

K-means clustering algorithm [5] partitions the data into a predefined number of clusters by minimizing the within-group sum of squares of distances calculated between the cluster representative and the data samples belonging to the cluster. Cluster representatives are initialized at the beginning of the algorithm and then both the data partitioning and the updating of the cluster representatives are performed iteratively as presented in Algorithm 2.

### Algorithm 2

```

begin
  Initialize the cluster representatives
  for i = 1 to convergence,
    Assign the sample to the closest cluster
    Calculate the representatives for the clusters
  end;
end

```

The cost function for the partitioning is defined as

$$J(\theta) = \sum_{i=1}^N \sum_{j=1}^K u_{ij} (x_i - \theta_j)^2 \quad (3)$$

in which  $N$  is the number of data samples,  $K$  is the number of clusters,  $\theta_j$  is the representative of the  $j^{th}$  cluster,  $x_i$  is the  $i^{th}$  data sample and  $u_{ij}$  is a scalar value which is assigned to 1 if  $x_i$  belongs to  $j^{th}$  cluster, otherwise it gets 0 value.

Randomized local search algorithm [6] generates the new cluster representatives by using a trial-error approach. At each iteration step a new candidate partition with the new representatives is generated as follows. One existing representative is replaced by a sample chosen randomly from the training data and two iterations of data partitioning and representative updating are performed. The cost for the fine-tuned candidate solution is calculated and compared to the previous cost, calculated before the last random swap. If the latest cost is lower than the old cost, the old representatives and cost are replaced by the candidate representatives and cost before the next iteration step. RLS is defined in an algorithmic form as follows

### Algorithm 3

```
begin
  Initialize the cluster representatives
  Assign each data sample to the closest cluster
  Calculate K, the new cluster representatives
  Calculate C, the cost for the partition
  for i = 1 : number of iterations,
    Swap randomly one representative from K
    for j = 1 : 2,
      Assign each data sample to the closest cluster
      Calculate the representatives for the clusters
    end;
    Calculate the cost for the new partition
  if the new cost < C,
    C = the new cost;
    K = the new representatives;
  end;
end;
end
```

The partition cost and the distances between data samples and the cluster representatives are defined in respect to Euclidean distance. Furthermore, the new representatives for clusters are the averages of the cluster members in both RLS and K-means clustering algorithms.

### Retrieval from a spectral image database

The retrieval approach used in this study represents spectral images by color histograms. A color histogram for a spectral image is generated by classifying the image spectra into the classes, whose representatives are constructed by the introduced unsupervised classification methods, and by generating a normalized histogram over these classes. The retrieval is based on dissimilarity calculations between the histograms corresponding to a query image and the images in a database. The ordered outputs are shown to a user as RGB-images. A diagram of retrieval from a spectral image database is shown in Fig. 1.

### The used data

The data used in the study includes 1269 reflectance

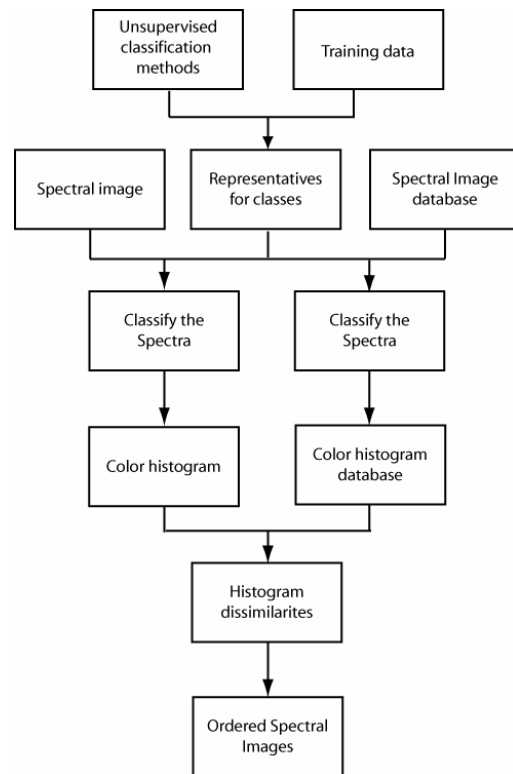


Figure 1. Retrieval from a spectral image database.

spectra of the color chips of the Munsell Book of Color Matte Finish Collection and a spectral image database [7] which are shortly introduced in this section.

The Munsell color system is one of the most widely used color order systems and Munsell data is often used in the area of color research. The data is well known for its uniform color space on trichromatic basis such as in CIEL\*a\*b\*. However, the data has also been used for many spectral applications such as color filters design for spectral image acquisition system [8], studies on spectral spaces and color spaces [9], the optimal sampling of color spectra [10] and the conversion between the reflectance spectra and Munsell data [11], and surface reflectances estimation [12].

The used Munsell spectral database consists of 1269 spectral reflectances acquired from the Munsell Book of Color Matte Finish Collection by a high precision spectrophotometer Perkin-Elmer lambda 9. The original spectral range was from 380 nm to 800 nm at 1 nm interval but for these purposes the data was restricted to spectral range from 400 or 420 nm to 700

nm at 5 nm interval, depending on the performed experiment. Every 20<sup>th</sup> spectral reflectance of the data and all reflectances converted into CIEL\*a\*b\* color coordinate system are shown in Figs. 2 and 3. The conversion from spectra to L\*a\*b\* coordinates is performed for CIE 1931 2 degree standard observer under CIE standard illuminant D65.

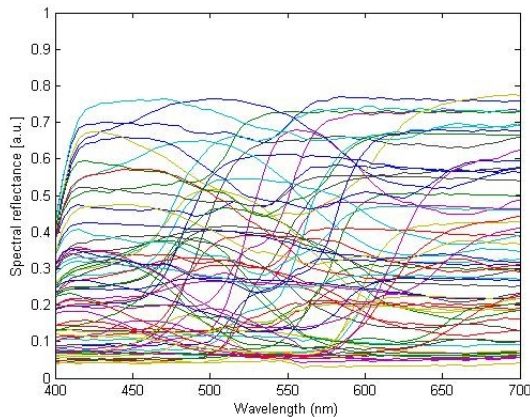


Figure 2. Every 20<sup>th</sup> spectral reflectance of Munsell data.

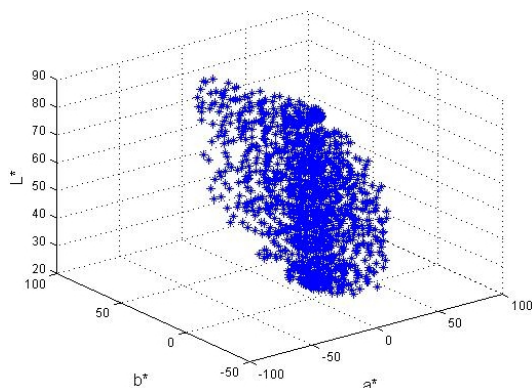


Figure 3. The Munsell data in CIEL\*a\*b\* color coordinate system.

The used spectral image database consisted of 226 images which were transformed into equal format, each image containing 57 components from 420 nm to 700 nm at 5 nm intervals. The images have been measured in the University of Joensuu (Finland) [7], Lappeenranta University of Technology (Finland) [13], Chiba University (Japan) [14], Saitama University (Japan) [8], Toyohashi University of Technology (Japan), Marine Biological Laboratory of Maryland (United States) [15], University of Bristol (United Kingdom) [16], University of East Anglia (United Kingdom) [17] and University of Minho (Portugal) [18-19]. The objects of the images include

printed magazine papers, postcards, business cards, human skin and faces, wood, buildings, color charts, icons and other paintings, fruits, flowers, leaves, bushes, forest, corals and both urban and countryside sceneries. In addition to real spectral images there exist also 24 synthetical images created by a virtual coloring technique [20]. The image database is shown in an RGB-format in Fig. 4.

## Experiments

In the first part of the experiments the Munsell data with wavelength range from 400 nm to 700 nm at 5 nm intervals was clustered by SOM, K-means and RLS algorithms. The number of generated classes varied from 2 to 60 and the initializations were done by choosing the first K samples from the data as proposed by McQueen [5]. The average color difference  $\Delta E_{ab}$  between the representatives and the classified Munsell spectra were calculated and the achieved results as a function of the used representative number are shown in Fig. 5. It can be seen that in the case of SOM the error will be stabilized quite quickly whereas in the cases of K-means and RLS the stabilization takes much longer time and the error decreases slowly but pretty surely till the end. In the case of 60 representatives the average color differences for SOM, K-means and RLS are 16.1, 8.4 and 8.2, respectively. These results indicate that the use of K-means and RLS might improve the retrieval results

To examine the usability of Munsell data as a training data compared to the training data collected from the database, altogether six sets of representatives with wavelength from 420 nm to 700 nm were constructed. The number of representatives was set to 50, the decision being based on the previous experiments in which this number was found out to be suitable for SOM with this kind of data. The representatives are shown in CIEL\*a\*b\* color coordinates in Fig. 6. The calculations are performed for CIE 1931 2 degree standard observer under CIE standard illuminant D65. In the cases of K-means and RLS, the representatives are more scattered to the color space than in the case of SOM. Besides, the representatives generated by SOM form a spiral in a space.



Figure 4. The used spectral image database in an RGB-format.

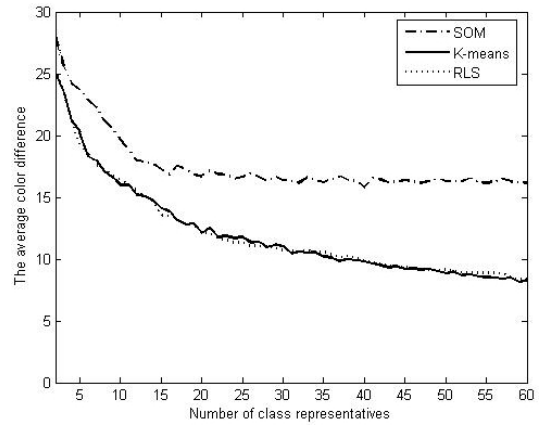


Figure 5. The average color differences as a function of number of representatives.

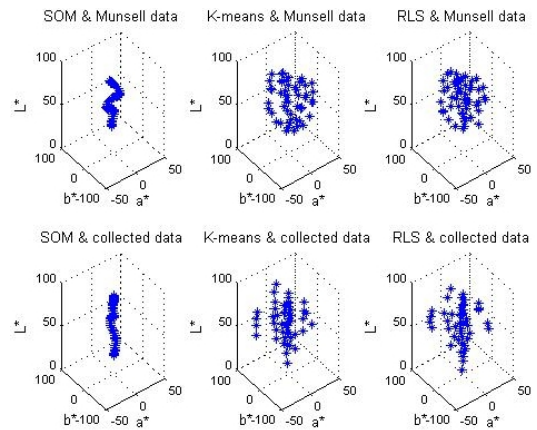


Figure 6. The representatives in CIEL\*a\*b\* color coordinate system

The retrieval from a database was performed by using representative sets and examples of ordered outputs achieved for two query images (real skin & printed paper) are shown Figs. 7 and 8. If the query image is included in the database, as in these cases, it will always be the first of the retrieved images. However, to save the space in horizontal plane we have now removed the query image from the set of retrieved images. Instead, the query image is shown on the top of the image and is followed by the ordered outputs. The leftmost image is the most similar to the query image in each output.

The database contains 11 images of hands and fingers, 21 images of faces and 6 images of those printed magazine pictures which can be considered to contain a reasonable amount of “artificial” skin. In the last

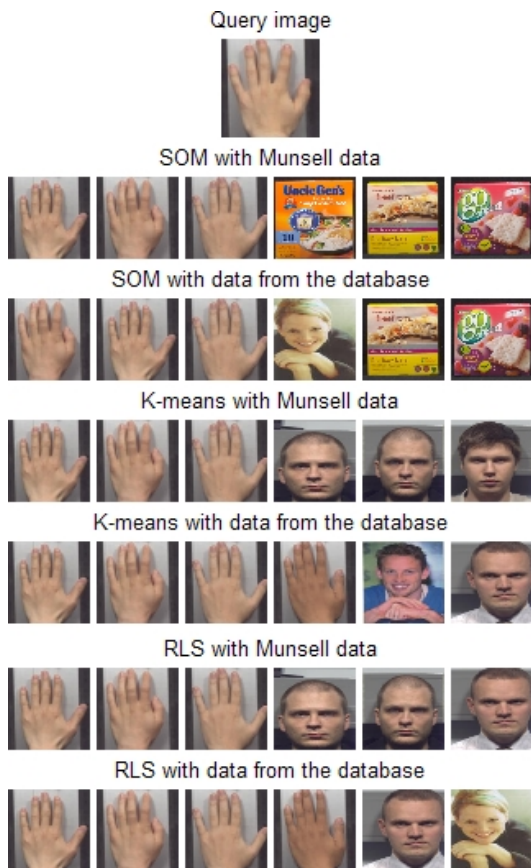


Figure 7. The ordered outputs in the cases of six representative sets.

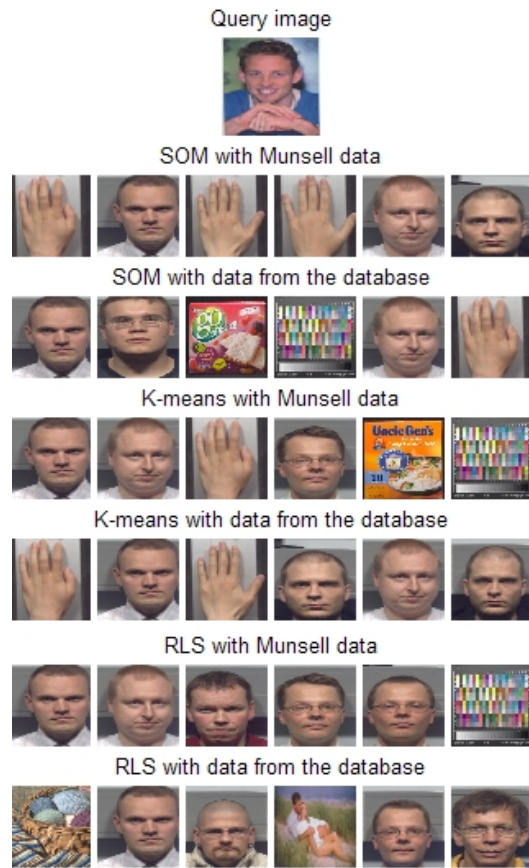


Figure 8. The ordered outputs in the cases of six representative sets.

part of the experiments the retrieval was performed for each of these images and the number of ordered output images was set to 15. A group of valid output images was defined to contain the mentioned images. The average percentages of achieved, valid output images for each set of representatives are shown in Fig 9, in which M and C correspond to Munsell data and data collected from the database, respectively.

## Discussion

The usability of Munsell data as a training data for three unsupervised classification algorithms used for class generation for color spectra was examined and the performance of these three algorithms compared to each other was evaluated. According to experiments, the performance of K-means was quite similar to RLS and in respect to the query image they both gave semantically more meaningful output images than SOM. When comparing the outputs in the cases of representatives generated by using Munsell data and data collected from the database, slightly

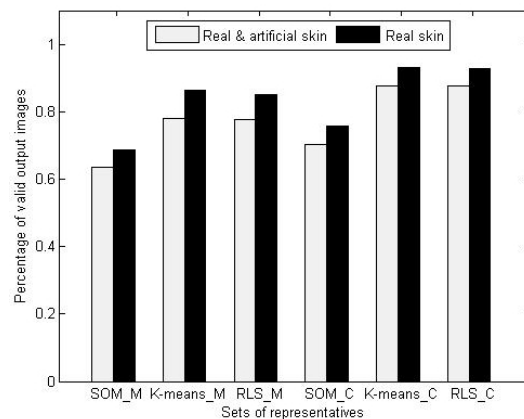


Figure 9. The percentages of achieved, valid output images.

better results were achieved by using the collected data. However, based on these results we assume that Munsell data could be used as a training data with sufficient success. The availability of the Munsell data enables the use of achieved results in comparison with other clustering methods for spectral data. Moreover, the availability of the data enables any researcher in the field to repeat the clustering process and possibly improve the results.

## References

1. Standard Object Colour Spectra Database for Colour Reproduction Evaluation (SOCS), TR X 0012:1998, Information Processing Divisional Council, Japanese Standards Association.
2. S. Borer and S. Susstrunk, Finding representatives in a large dataset of spectral reflectances:  
<http://citeseer.ist.psu.edu/684606.html>
3. O. Kohonen, M. Hauta-Kasari, J. Parkkinen and T. Jääskeläinen, Organizing spectral image databases by using self-organizing maps, *Journal of Imaging Science and Technology*, 49, p. 431-441, (2005).
4. T. Kohonen, *Self-Organizing Maps*, Springer. Third extended edition, Berlin Heidelberg 2001.
5. J. B. McQueen, Some methods for classification and analysis of multivariate observations, *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, p. 281-297, (1967).
6. P. Fränti and J. Kivijärvi, Randomized local search algorithm for the clustering problem, *Pattern Analysis and Applications*, 3, p. 358-369, (2000).
7. Spectral database, University of Joensuu Color Group, <http://spectral.joensuu.fi>
8. M. Hauta-Kasari, K. Miyazawa, S. Toyooka and J. Parkkinen, Spectral vision system for measuring color images, *J. Opt. Soc. Am. A*, 16, p. 2352-2362, (1999).
9. R. Ramanath, R. G. Kuehni, W. E. Snyder and D. Hinks, Spectral spaces and color spaces, *Color Research & Application*, 29, p. 29-37, (2004).
10. J. Lehtonen, J. Parkkinen and T. Jaaskelainen, Optimal sampling of color spectra, *J. Opt. Soc. Am. A*, 23, p. 2983-2988, (2006).
11. H. Laamanen, T. Jääskeläinen and J. Parkkinen, Conversion between the reflectance spectra and Munsell notations, *Color Research & Application*, 31, p. 57-66, (2006).
12. C.-H. Lee, B.-J. Moon, H.-Y. Lee, E.-Y. Chung, Y.-H. Ha, Estimation of spectral distribution of scene illumination from a single image, *Journal of Imaging Science and Technology*, 44, p. 308-320, (2000).
13. V. Botchko, J. Auvinen, O. Mäkinen, H. Kälviäinen and J. Parkkinen, Parametric multispectral texture modeling, In proceedings of 11th scandinavian conference on image analysis, SCIA'99, Greenland, p. 763-769, (1999).
14. T. Fujimaki, K. Ishii, N. Tsumura and Y. Miyake, Proposals of standard spectral image and its application to designing of CCD camera, In proceedings of IS&T PICS Conference, Rochester, p. 496-499, (2003).
15. C. A. Parraga, G. Brelstaff, T. Troscianko and I. R. Moorehead, Color and luminance information in natural scenes, *J. Opt. Soc. Am. A*, 15, p. 563-569, (1998).
16. C.-C. Chiao, T. W. Cronin and D. Osorio, Color signals in natural scenes: characteristics of reflectance spectra and effects of natural illuminants, *J. Opt. Soc. Am. A*, 17(2), p. 218-224, (2000).
17. G. D. Finlayson, S. D. Hordley and P. Morovic, A multi-spectral image database and an application to image rendering across illumination, In proceedings of the third international conference on image and graphics, Hong-Kong, China, (2004).
18. S. M. C. Nascimento, F. P. Ferreira and D. H. Foster, Statistics of spatial cone-excitation ratios in natural scenes, *J. Opt. Soc. Am. A*, 19(8), p. 1484-1290, (2002).
19. D. H. Foster, S. M. C. Nascimento and K. Amano, Information limits on neural identification of coloured surfaces in natural scenes, *Visual Neuroscience*, 21, p. 331-336, (2004).
20. V. Botchko, S. Nakauchi, J. Parkkinen, H. Kälviäinen, Multispectral texture derivation in virtual coloring, in M. Pietikäinen (Ed.) *Texture Analysis in Machine Vision*, World Scientific Publishing Co., Singapore, (2000).