Methods to organize spectral image database

Oili Kohonen[1], Markku Hauta-Kasari[2], Kanae Miyazawa[3], Jussi Parkkinen[2], and Timo Jääskeläinen[1]
[1] Department of Physics, [2] Department of Computer Science, University of Joensuu, P.O.Box 111, FIN-80101 Joensuu, Finland. [3]Department of Information and Computer Sciences, Toyohashi University of Technology, 1-1 Hibarigaoka Tempaku, Toyohashi 441-8580, Japan

Abstract

Techniques for searching images from a spectral image database and calculating the distances between spectral images are proposed. The techniques are based on one- and two-dimensional Self-Organizing Map (SOM). For one-dimensional SOM, the Best Matching Unit (BMU) histogram for every spectral image in a database is created, and images of a database are ordered according to the histogram similarity. Two-dimensional SOM is trained by using BMU-histograms as a training data and the distance between spectral images is defined based on their location on the map. The results using real spectral image database are given.

1. Introduction

Spectral imaging has faced a growing interest during last few years. Especially the development of computer-based multimedia systems have created a real need to produce color precisely under different illuminations. Even though metameric imaging is a cheap and practical way to achieve a color match for a certain illumination, the spectral imaging is needed to achieve a color match for all observers across the changes in the illumination.

High data volume is a significant disadvantage of spectral imaging. In metameric imaging only 3 channels are needed, but in the spectral imaging the amount of used channels varies from 4 to several hundreds, depending on a needed spectral resolution. When the spectra are measured from 400 nm to 700 nm, the typical numbers of channels are 31 and 61.

At the moment only a few spectral image databases are publicly available but the amount and the size of them are expected to increase in the future due to the rapid development of spectral imaging systems [1]. In consequence of the high data volume of spectral images, fast methods for searching images in the spectral image databases will be needed. For RGB image databases, techniques such as PicSOM [4] and QBIG [5] exist already.

A searching technique in a spectral image database using one-dimensional Self-Organizing Map (SOM) is proposed in [1]. There a Best-Matching Unit (BMU) histogram is defined and a query from a database is realized according to the BMU-histogram similarity. In this study the number of similarity measures for one-dimensional SOM is increased and the searching technique is expanded into the two-dimensional SOM.

The paper is organized as follows. In chapter 2 the creation of a histogram database and the searching technique based on one-dimensional SOM are presented. The principles of distance calculations and two-dimensional SOM are introduced in chapter 3. The used spectral image database is presented in chapter 4. Chapter 5 includes the experimental results and the conclusions are given in chapter 6.

2. Searching Technique

For searching, the training data for SOM is created by selecting spectra from the chosen spectral images. Spectra are selected randomly and the number of spectra is chosen empirically. After training, the SOM contains spectra in an order [3]. For each pixel of the image we calculate the BMU. This is defined for the input spectrum, i.e vector x as follows:

$$\|x - w_{\mathrm{BMU}}\| = \min_i \|x - w_i\|, \qquad (1)$$

in which w_i and w_{BMU} indicate the weight vector of i^{th} unit and the winner unit, respectively. Furthermore, BMU is defined as an index number that corresponds to w_{BMU}. Next, BMU-histograms for spectral images are created. The histograms are normalized by the number of pixels in an image. This process is done for each of the images and a database of BMU-histograms is got as a result. The size of the histogram database matrix is $n \times m$, in which n and m are the number of used spectral images and the amount of map units, respectively.

The search in the spectral image database is done as follows. The spectral image is selected and the BMU-histogram is generated by using the map, by which the histogram database was generated. Next, the created BMU-histogram is compared with the histogram database. The distances between the histograms are calculated and the images are ordered by these distances. If the selected image is included in the database, the smallest distance is 0. The results of the search are shown to a user as RGB-images.

3. Distance Calculations

Distance calculations are done using euclidean distance, energy, maximum peak location and Kullback-Leibler distance as distance measures. The distances between two histograms, H_1 and H_2, in above mentioned metrics are described as follows:

$$\mathrm{EuclideanDistance} = \sum (\mathrm{H_{1i}} - \mathrm{H_{2i}})^2, \qquad (2)$$

$$\mathrm{Energy} = \mid \sum \mathrm{H_{1i}^2} - \sum \mathrm{H_{2i}^2} \mid, \qquad (3)$$

$$\mathrm{MaximumPeakLocation} = \mid \mathrm{L_1} - \mathrm{L_2} \mid, \qquad (4)$$

in which L_1 and L_2 are the indices of the maximum values of compared histograms.

$$\mathrm{Kullback-LeiblerDistance} = \sum \mathrm{H_{1i}} \log\left(\frac{\mathrm{H_{1i}}}{\mathrm{H_{2i}}}\right). \qquad (5)$$

In case of one-dimensional SOM, H_1 and H_2 represents BMU-histograms that are created for every image in a used spectral image database.

In the case of two-dimensional SOM, the one-dimensional SOM is generated first, as described above. The generated histogram database is used as a training set for the two-dimensional SOM. After creation of two-dimensional SOM, the distance calculations in a created map using Equations 2–5 are done as follows. The spectral image is selected and it's BMU-histogram is generated. The BMU is calculated for the new BMU-histogram and every histogram in the database. The distances between the selected image and the images presented in a histogram database are calculated as a sum of the differences between the corresponding components of those two histograms, which corresponds calculated BMUs in the two-dimensional map. If the selected image is included in the database, or if any other image in the database has the same BMU as the selected image, the smallest distance is 0.

4. Spectral Image Database

In this study a database of 106 spectral images was used. The images have been measured at the University of Joensuu (Finland) [8], Lappeenranta University of Technology (Finland), Chiba University (Japan), Saitama University (Japan), University of Bristol (United Kingdom) and at Marine Biological Laboratory (Maryland, USA). The images have been filtered into equal format: 61 spectral components with the spectral range from 400 nm to 700 nm at 5 nm intervals. The size of the images varies from 3 megabytes to 56 megabytes. The objects of the images are for example skin, corals, fruits, plants, printed magazine pictures, logos of business cards and GretagMacbeth colorchecker. Some of the images were created synthetically.

5. Experiments

The calculations were done by using a SOM_PAK-software package [2] and a SOM toolbox for Matlab [6]. One-dimensional and two-dimensional SOM-maps were created by using spectral images and images weighted by human visual sensitivity function [7]. In all cases the topology type used in the map was hexagonal and the learning rate function type was linear. In the case of one-dimensional SOM 10 000 spectra from each image were selected randomly as a training data for SOM. To retain the theoretical possibility that every spectrum, included in the training data, could be chosen at least once, the minimum number of epochs has to be more than 1 000 000.

The one-dimensional SOM, which consisted of 50 units, was trained by using 2 000 000 epochs in the ordering phase and 4 000 000 epochs in the fine tuning phase. The initial radius of the training area was 50 and the learning rates in the ordering phase and in the fine tuning phase were 0.9 and 0.02, respectively. The histogram similarities were calculated by using euclidean distance, energy, maximum peak location and Kullback-Leibler distance as distance measures and the spectral images were ordered according to the similarity. The results in the case of euclidean distance are shown in Figures 1 and 2. The image of young lady, shown in the left upper corner, is used as a reference image and the images from left to right and from top to down are the images in ascending order according to dissimilarity. It can be seen that ordering using spectral images differs from the one in which the images weighted by human visual sensitivity function are used. The scaled distances between the reference image and every image in the used database for spectral images and spectral images weighted by human sensitivity function are shown in Figure 3. The image indices are ordered corresponding to the histogram difference.

Figure 1: *Ordered output for spectral images in case of euclidean distance as a distance measure.*

Figure 2: *Ordered output for spectral images weighted by human sensitivity function in case of euclidean distance as a distance measure.*

Ordered output for 10 first images in the case of maximum peak location, energy and Kullback-Leibler distance as distance measures are shown in Figures 4–6. In these cases the spectral images have been weighted by human sensitivity function. It can be seen that the images as well as the ordering of the images varies a lot between the cases.

In the case of two-dimensional SOM, the size of the produced map was 20 times 20 units. The initial radius of the training area was 20 and the learning rates in the ordering phase and in the fine tuning phase were 0.9 and 0.02, respectively. The BMUs for the histogram database were calculated by using euclidean distance as a distance measure. The images are placed to the map according to the BMUs and the euclidean distances between the chosen reference image and every image in the database are calculated as described in chapter 3. Due to the restricted amount of space, the whole two-dimensional SOM that contains the images cannot be shown. A small part of it is shown in Figure 7. The scaled distances between the reference image and every image in the used database are shown in Figure 8.

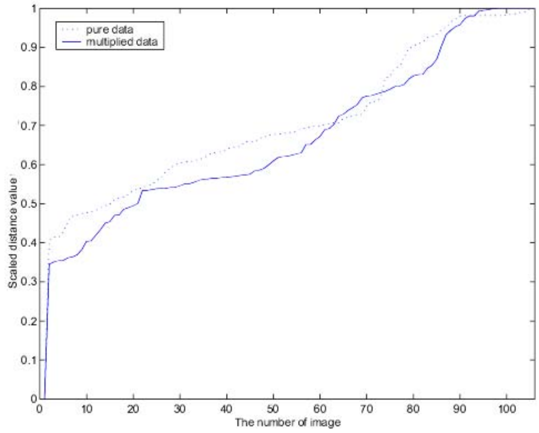

Figure 3: *The scaled distances between the reference image and every image in the used database for spectral images and images weighted by human spectral sensitivity function.*

Figure 4: *Ordered output for spectral images weighted by human sensitivity function in case of maximum peak location as a distance measure.*

Figure 5: *Ordered output for spectral images weighted by human sensitivity function in case of energy as a distance measure.*

Figure 6: *Ordered output for spectral images weighted by human sensitivity function in case of Kullback-Leibler distance as a distance measure.*

Figure 7: *The placements of images in two-dimensional SOM.*

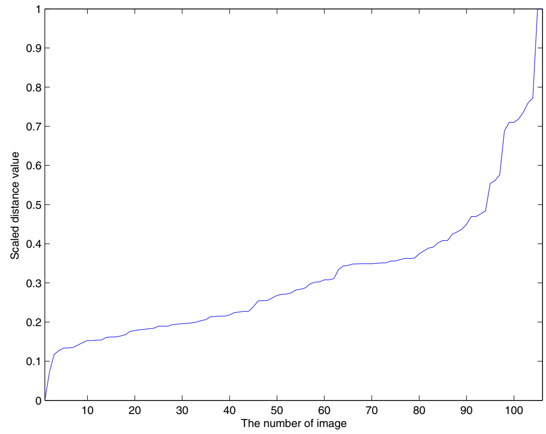

Figure 8: *The scaled distances between the reference image and every image in the used database in the case of two-dimensional SOM.*

6. Discussion

A searching technique in a spectral image database with different distance measures was tested. In addition, a technique for calculating the distances between spectral images by using the two-dimensional SOM was proposed. It was shown that the proposed features are useful in image search. The structure of the database is different for spectral images than for spectral images weighted by human visual sensitivity function. Also, the structure of the database is highly dependent on the used distance measure.

Each of the features contains advantages and disadvantages. For an example euclidean distance and location of maximum peak are highly place dependent and a small shift in a histogram may cause high distance value even though the shapes of the compared histograms would be very similar. On the other hand, the distance value between two histograms that have very different shapes, may be really small in the case of energy. Due to above mentioned things, the combining of features might be wise.

Next goal in this research is to study the importance of human visual function normalization, to test more features for BMU-histogram similarity calculation and to combine some features.

References

[1] Hauta-Kasari, M., Miyazawa, K., Parkkinen, J., Jääskeläinen, T.: Searching Technique in a Spectral Image Database. 13th Scandinavian Conference on Image Analysis, Göteborg, 2003.

[2] Kohonen, T., Hynninen, J., Kangas, J., Laaksonen, J.: SOM_PAK: The Self-Organizing Map Program Package . Technical Report A31, Helsinki University of Technology, Laboratory of Computer and Information Science, Espoo, Finland (1996)

[3] Miyazawa, K., Hakkarainen J., Parkkinen J., Jääskeläinen, T.: Ordering of color spectra for digital image enhancement. In Proceedings, International Congress of Imaging Science (ICIS'02), Tokyo, Japan, May 13.-17., (2002), 492-293.

[4] Laaksonen, J., Koskela, M., Laakso S., Oja, E.: Self-Organizing Maps as a Relevance Feedback Technique in Content-Based Image Retrieval. Pattern Analysis & Applications 4, 2001, 140–152.

[5] QBIG – IBM's Query By Image Content: http://wwwqbic.almaden.ibm.com/(January 18, 2004)

[6] SOM Toolbox, a software package for Matlab 5: http://www.cis.hut.fi/projects/somtoolbox/ (January 18, 2004)

[7] Wyszecki, G., Stiles, W. S.,: Color Science, Wiley, New York, 1982.

[8] http://cs.joensuu.fi/∼ spectral/ (January 18, 2004)