From Content-based Image Retrieval to Example-based Image Processing

Guoping Qiu
School of Computer Science, The University of Nottingham
qiu@cs.nott.ac.uk
26 May 2004

Abstract

This paper presents a novel application framework for content-based image retrieval (CBIR) technology. We use CBIR to (semi-) automatically obtain image clusters containing certain homogenous image statistics, and then use the images in the clusters as examples for learning (or example) based image processing. We demonstrate the potential of the new image processing paradigm by developing applications for color image rendering, correction and enhancement.

1 Introduction

Content-based image indexing and retrieval (CBIR) [1] has been a topic of considerable research interest for nearly 20 years. Traditionally, CBIR is designed for managing large image databases by developing tools to help users to effectively organize large collections and to find images as quickly as possible.

Example-based image processing, sometimes also known as learning-based or recognition-based image processing appears in the literature in various disguises and have applications in vision, image processing and graphics. Qiu [2, 3] showed one of the earliest examples of learning-based images processing with applications to image coding and spatial resolution enhancement. Freeman et al also studied learning based approaches to super-resolution and general low-level vision [4, 5]. Baker and Kanade studied learning based approach to resolution enhancement for a specific class of object (faces) [6]. In computer graphics, there is much work in image-based rendering including texture synthesis [8], image analogies [7], and learning video processing by example [9].

In this paper, we present a novel framework that uses CBIR for developing example-based image processing applications, the schematic of which is illustrated in Figure 1. For a given input image (to be processed), we use content-based image retrieval to select example images either automatically or interactively. The purposes of the processing can be varied from making the input image to take on some of the statistical characteristics of the retrieved example images to using the example images to enhance the appearances of the input image.

As an example of this new image processing framework, in this paper, we use a recently developed image clustering technique [11] to first cluster a large image database into image clusters, each contains images of certain homogeneous property such as color or texture. We then transfer the color statistics of the image clusters into the input image to correct and enhance the color appearances of the input image.

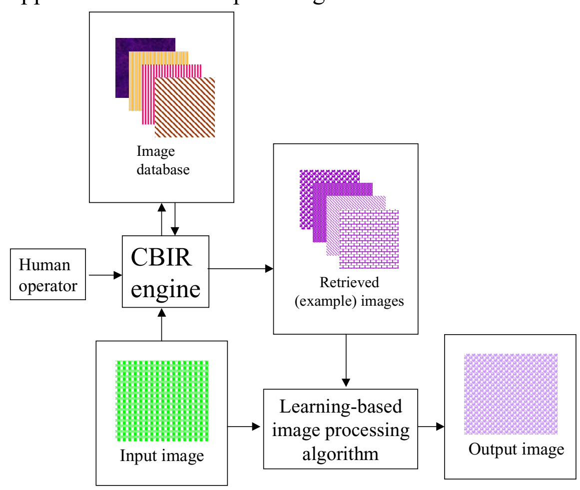

Figure 1, Schematic of CBIR for learning based image processing applications

2 Image Retrieval based on Image and Feature Co-clustering

To obtain the example images for learning based image processing, there are various possible methods. It is possible to use example based image retrieval to retrieve images similar to the image to be processed. Another possibility is the cluster the images in the database into clusters containing certain homogenous visual properties such as color or texture. According to the desired processing effects, we can then select an appropriate cluster of images as example for processing the input image. In this paper, we take the second approach by first cluster the image database.

We use a recently developed image clustering technique. Details of this image clustering technique has been described elsewhere [11]. Briefly, we first use an image appearance-indexing model [10] to capture the color and spatial pattern (texture) statistics of the image. Bipartite graph is then used to model the appearance prototypes and the images simultaneously. Image and appearance prototype clustering is achieved by cutting the bipartite graph. Figure 2 shows one of the clusters created by the algorithms from a database containing 6,400 images. More clusters can be found on our website[1].

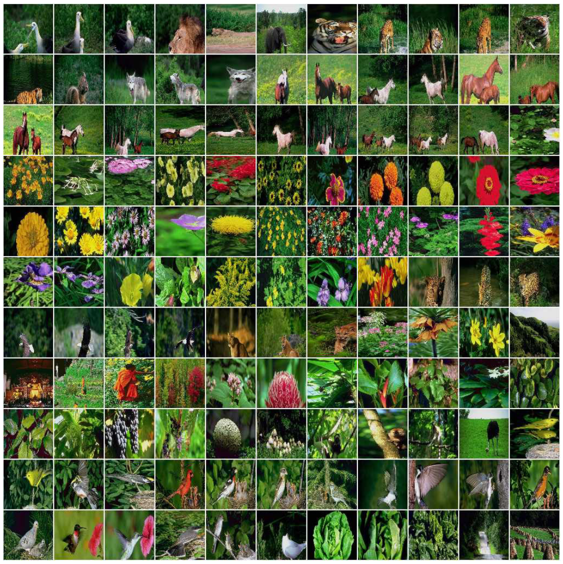

Figure 2, Thumbnail images in a cluster obtained by image and feature co-clustering a 6,400 image database

3 Application to color image enhancement

We illustrate the application of the framework by applying it to color image enhancement. In [12], it has been demonstrated that it is possible to transfer the color statistics from one image to another to make one image to take on the color appearance of another image. Such technique can also be used for color correction. However, one of the difficulties of the method is to find an appropriate source (example) image. If the source images were not chosen carefully, the color transfer will fail. Moreover, manual selection of source image totally depends on subjective judgement and can be laborious.

Instead of relying on manually selecting source images, our method can automate (or semi-automate) the process. More importantly, we can select large numbers of images with similar color statistics. Large samples should make the statistics much more reliable, which should also better reflect real world events.

For a given input image, we transfer the color statistics of an appropriate chosen image cluster to the input image. We use the de-correlated color space, termed $l\alpha\beta$ in [12] for the processing. The relation between RGB and de-correlated $l\alpha\beta$ can be written as

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} 0.5774 & 0.5774 & 0.5774 \\ 0.4025 & 0.40825 & -0.8165 \\ 0.7071 & -0.7071 & 0.0000 \end{bmatrix} \begin{bmatrix} \log L \\ \log M \\ \log S \end{bmatrix} \quad (2)$$

l is the achromatic signal, α and β are two chromatic signals. For color correction and enhancement, we keep the images achromatic signal unchanged, and make the average α and β of the input image equal to the average α and β of all the images in the cluster.

Let $m_{\alpha cluster}$, $m_{\beta cluster}$ be the average chromatic signals of all images in the example image cluster, $m_{\alpha i}$, $m_{\beta i}$ be the average chromatic signals of the input image to be processed, l', α', β' be the output color corresponding to the input color l, α, β, we have following processing relations

$$\begin{aligned} l' &= l \\ \alpha' &= \alpha - m_{\alpha i} + m_{\alpha cluster} \\ \beta' &= \beta - m_{\beta i} + m_{\beta cluster} \end{aligned} \quad (3)$$

3.1 Results

We use 240 images in a cluster created by the image and feature co-clustering algorithm (part of the cluster is shown in Figure 2) as example to process a number of color photographs. Note that other clustering and CBIR methods can also be used to retrieve appropriate examples. Image in this cluster contains outdoor scenes with green plants and grass dominated the images. These example images should capture the color statistics of similar outdoor scenes. One scenario where transferring the color statistics of this cluster would be useful is in the restoration of old photographs of outdoor scenes where the colors on the photos have faded somewhat. It would also be useful to render a winter outdoor scene to have the look of a spring outdoor scene. Another possibly useful application is to render an outdoor scene taken in a cloudy day or under the shadow, which will cause the photographs to have a dull color appearance, to have more vivid color appearance.

Figure 3 shows an image taken in a public park in central England in a winter day, we processed the image by making the photograph's average chromatic signals equal to those of all images in the cluster shown in Figure 2, see equation (3). It is seen that the output image has been transferred from a winter scene to have the look of a spring scene.

Figure 4 show a patch of grass taken at dusk in a cloudy day. The color of the image appears very dull. By transferring the average colors in the image cluster of Figure 2 onto this image, we have brought the colors of the image to life.

[1] www.cs.nott.ac.uk/~qiu/research/nips2003ifcc.html

Figure 5 shows more images, which have been deliberately distorted. We then transfers the color statistics of the image cluster in Figure 2 to these color distorted images, in all cases, we were able to correct the images to have more realistic appearances.

Figure 3, Rendering color photographs. Top: Original photo taken in a winter day using a digital camera (Canon Power Shot Pro 70). Bottom: Rendered by making the original's chromatic signal to take on the statistics of 240 images as shown in Figure 2.

It is important to note that these input images differ quite significantly. Using the same color statistics, we were able to correct these different images. An interesting question arises, does outdoor scenes, or any other types of natural scenes, fundamentally contain some intrinsic color statistics? If so, would it be possible to capture these intrinsic statistical characteristics from large collections of photographs of these scenes? How to automatically choose such a collection of images that could be used to learn the intrinsic statistics of a given type of scenes would be a challenging and interesting task.

4 Concluding remarks

In this paper, we have proposed a novel application framework for content-based image retrieval. We use CBIR technology to search for example images for learning (example) based image processing. We have used image clustering and color processing as a concrete application example to demonstrate the potential of our new framework.

Figure 4, Correct image color. Top: Original photo taken at dusk in a cloudy day using a digital camera (Canon Power Shot Pro 70). Bottom: Color corrected by making the original's chromatic signal to take on the statistics of 240 images as shown in Figure 2.

References

[1] A. W. M. Smeulders et al, "Content-based image retrieval at the end of the early years", IEEE Trans PAMI, vol. 22, pp. 1349 - 1380, 2000

[2] G. Qiu, "A progressively predictive image pyramid for efficient lossless coding", IEEE Trans. on Image Processing, Vol. 8, No.1, pp. 109 – 115, 1999

[3] G. Qiu, "Inter-resolution look-up table for improved spatial magnification of images", Journal of Visual Communications and Image Representation, vol. 11, pp. 360 - 373, Academic Press, November 2000

[4] W. T. Freeman, T. R. Jones, and E. C. Pasztor, "Example-based super-resolution", IEEE Computer Graphics and Applications, March/April, 2002

[5] W.T. Freeman, E.C. Pasztor, and O.T. Carmichael, "Learning Low-Level Vision," Int'l J. Computer Vision, vol. 40, no. 1, Oct. 2000, pp. 25-47

[6] S. Baker and T. Kanade, "Limits on Super-Resolution and How to Break Them", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 9, September, 2002, pp. 1167 – 1183

[7] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, D. H. Salesin, “Image Analogies”, SIGGRAPH 2001 Conference Proceedings. Los Angeles, California. August 12-16, 2001. pp. 327-340

[8] A. A. Efros and T. K. Leung, "Texture Synthesis by Non-parametric Sampling", ICCV 99

[9] A. Haro and I. Essa, “Learning video processing by example”, Proc. 16th ICPR, pp. 487-491, 2002,

[10] G. Qiu, “Appearance indexing”, Proc. ICASSP 2003, vol. III, pp. 597 – 600, April 2003

[11] G. Qiu, "Image and feature co-clustering", ICPR2004, 17th International Conference on Pattern Recognition, Cambridge, United Kingdom, 23 - 26 August 2004

[12] E. Reinhard etal, “Color transfer between images”, IEEE Computer Graphics and Applications, Sept/Oct. 2001, pp. 34 – 41

Figure 5, Color correction examples

Color distorted images (original input)

Color corrected image (processed output)

Color distorted images (original input)

Color corrected image (processed output)

Color distorted images (original input)

Color corrected image (processed output)