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Classification of Images for Automatic Colour Correction

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Abstract

The ways in which image classification can be utilised in automatic colour correction are discussed. Before images can be classified, a restricted set of numeric features must be extracted from image data. Many of these features can be defined on the basis of the statistical distribution of the colour values of pixels. In some cases, however, spatial image properties are also needed. In automatic colour correction, image classification guides the selections made within and between different correction elements including the adjustment of primary colour components, adjustment of tone rendering in Lsa colour space[1], grey balance adjustment and skin colour correction.

Introduction

An automatic source independent algorithm for the correction of colour images has been developed in the Laboratory of Graphic Arts Technology at the Helsinki University of Technology (HUT).[2] Development of the algorithm by solely heuristic techniques has revealed that different images need different ways of manipulation. Therefore, one of the main aims of current research is finding means of classifying images in order to achieve the best results with respect to quality and computational complexity for each individual image. The principal phases of image classification and automatic image adjustment are illustrated in Figure 1, which is based on Finnish patent application[3] for automatic colour correction. The visually evaluated performance of the correction software has been recently discussed in references[4,5].

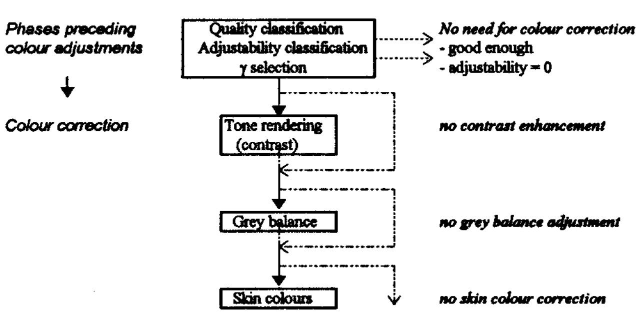

Figure 1. Principal phases of automatic colour correction.

Even though in Figure 1 the general quality and adjustability classification is a separate phase preceding all actual image adjustment phases, this kind of classification can also be used as a pre-processing stage for each colour adjustment element. For example, if general adjustability is poor because of disturbing noise in the image data, it does not necessarily mean that all colour adjustment elements are incapable of improving the visual image quality. Some adjustments may still work rather well even if others caused deterioration of image quality resulting from, say, visually disturbing enhancement of noise.

Basic Tasks of Image Classification in Automatic Colour Correction

In source independent colour image correction (the technical origin of the image is not known), there is considerable variability in image quality and content. Some images do not need any correction, whereas others require several enhancements. As our aim is good qualitative and quantitative performance of the automatic correction procedure, it is useful to classify the images at an early phase of the procedure, ensuring that we do not unnecessarily use a complex algorithm when a simpler one is sufficient. For certain adjustments, e.g. contrast enhancement, amplification of the quantisation error or noise must also be taken into account, and so the images have to be classified prior to correction depending on the strength of the adjustments they can tolerate. (This image property is called "adjustability" in Figure 1.) The needs for classification are thus very practical and closely related to the particular correction algorithms being used. We can distinguish at least four types of classification, which are not, however, totally independent of each other:

• classification with respect to some property which we desire to correct (whether the image is already sufficiently good and does not require adjustment with respect to that property),

• classification with respect to properties which we do not correct but which may be enhanced due to correction and spoil the image (e.g. noise or false contours),

• classification for finding the most economical method of correction (e.g. for some images, selection of right gamma for the RGB components is sufficient, while for others more complicated adjustments and a different colour space are required),

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• a rough classification according to image content, permitting the smart selection of a correction algorithm for each situation (an image containing a large portion of green vegetation, for instance, must not be interpreted as having a greenish colour cast). This is based on the assumption that images of different content have different optimum colour rendering.

Input Features used in Image Classification

The fundamental problem with classification is the reduction of an image into a set of computational features which form a sufficient basis for the classification. One possible aid for this is visualisation with neural networks, as illustrated in Figure 2. It shows a self-organising map of randomly selected (original) pictures. Here, we have made the assumption that the statistical distribution of pixels within an image (the "histogram") contains all the information relevant to classification. Figure 2 shows that, in most cases, good and bad images are located in different areas of the map.

The colour histogram, being easy to compute, is a convenient starting point for features and thus recommended wherever possible. Yet the classification with respect to certain image properties, e.g. sharpness or noise level, which are key features in evaluation of adjustability, requires consideration of spatial information as well. This is true also for skin colour recognition, as discussed in reference [6].

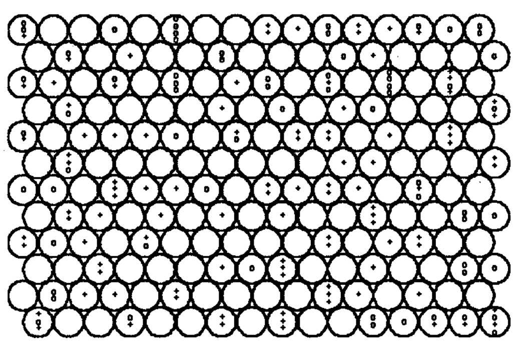

Figure 2. A self-organising map trained with colour distributions and the location of the training images on it. (Each '+' represents a visually "good" image and each 'o' a "bad" image.)

Selection of Gamma

γ-selection is quite different in nature from other image classification elements preceding actual colour adjustment. In fact it is a matter of taste whether the selection of gamma should be considered as image pre-processing or as an colour adjustment phase. Unlike in the case of general quality or adjustability considerations, the result for the classification (a γ value) is directly used as the colour adjustment parameter. The aim is simply to select automatically the most suitable monitor γ (gamma) for each individual RGB image. Sometimes this gamma is known, and automatic gamma selection is not needed. The basic assumption is, however, that the only information known about the images is the digital RGB values of pixels. In practice, the gamma of the test monitor was 1.0 all the time, but new values (R', G', B') were calculated from the original RGB values according to formula[1]. All (other) colour adjustments were based on these new RGB values.

$$
\begin{aligned}
R' &= R^{\gamma} \\
G' &= G^{\gamma} \\
B' &= B^{\gamma}
\end{aligned}
\qquad (1)
$$

Selection of gamma greatly affects the colours of an image. Changing gamma changes the brightness, saturation and hue values of an RGB image in a way that is very difficult to predict and attain with adjustments made in "hue, saturation, brightness" -type of colour spaces[1] (such as Lsα). The test where the appropriate gamma was selected visually for a large number of different images from different image sources showed that different images need different gammas as illustrated in Figure 3. However, if a constant general-purpose gamma had to be selected, a good γ value would be ≈ 1.4.

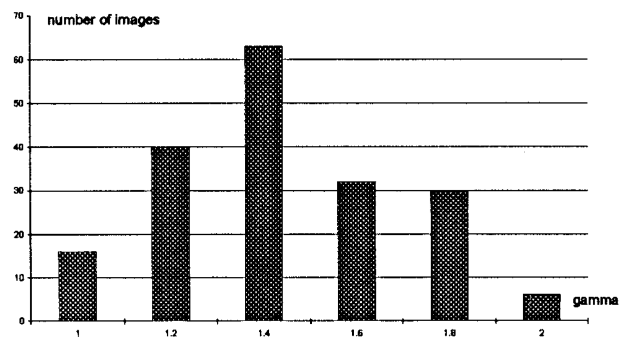

Figure 3. Distribution of visually found gamma values for a set of 187 RGB images

In visual classification (unlike in Figure 3) nine γ classes (1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.8, 2.0) were used. As the relatively small γ differences between these classes were considered visually remarkable, it would have been desirable if automatic classification had been capable of reliably finding the right classes for test images (not used in training). Unfortunately, this happened only in 20% of the cases. The classification was carried out using a radial basis network trained with 93 images with input features extracted solely from a histogram of a special brightness related parameter. Even though a low classification error rate could not be attained with the nine gamma classes mentioned earlier, the classification gave a significantly lower average γ error (between the selected and the visually defined desirable gamma) than any constant gamma value.

Discussion and Conclusions

Statistical image properties based on colour histograms are useful input features in image classification used for colour correction purposes. In practice, input features

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have decisive effect on the success of network training and have to be carefully selected depending on the purpose of classification. For example, when the aim is recognition of images containing human beings, sky or vegetation, more attention should be paid to the dominant colours than to lightness distribution. On the other hand, when classifying images according to grey balance, it is essential to utilise the distribution of low saturation colours and, to a large extent, ignore the most saturated ones. It is also important to properly select the manner in which the neural network measures similarity or dissimilarity between histograms or feature vectors extracted from them.

The automatic colour correction algorithm contains many different elements such as the adjustment of primary colour components (in RGB space), adjustment of tone rendering in Lsα colour space, grey balance adjustment and skin colour correction. Before images are automatically adjusted, image classification determines certain critical selections made between these colour correction elements. Use of neural networks for this purpose makes for significant improvements in both the quantitative and qualitative performance of the algorithm. In practice, image classification decreases computation times because unnecessary adjustments can be eliminated. It also improves image quality because the most appropriate correction elements can be selected on the basis of image characteristics.

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