Dimensionality Reduction for Colour Based Pixel Classification

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Abstract

In digital images, providing classification based on colour, hue or spectral angle is a problem usually solved by combining a variety of pre-processing steps, as well as object wise classifiers. We have developed a method for transforming colour or multispectral image data to a 1D colour histogram with respect to the digital characteristics of intensity measurements. Classification is then reduced to 1D histogram segmentation which is a simpler problem. The proposed method, based on ideas of spectral decomposition, was previously applied in dual-colour fluorescence microscopy for quantification and detection of colocalization insensitive to cross-talk. In this paper the principle is expanded to unsupervised colour based pixel classification algorithms in hue-saturation-lightness or luminance-chrominance colour spaces.

1. Introduction

Image segmentation, one of the most important steps leading to the analysis of processed image data, could be defined as clustering or grouping in spatial domain of the image. It often combines several higher-level processing techniques, and begins with pixel classification based on the analysis of intensity and spectral properties of all relevant pixels [1, 2]. A well known pixel classification algorithm for grey-level image analysis that leads towards image segmentation is intensity thresholding.

Initial pixel classification becomes a more complex problem for colour and multispectral images since information is held in colour rather than in intensity. In the three-color case, colour spaces should preferably have decoupled colour and intensity information (e.g., HSI, YUV, YIQ, YCbCr, etc) since physically correct colour based classification, invariant to illumination changes, is equivalent to slicing the colour space with half-planes emanating from the achromatic axis.

1.1. Colour histogram

Colour histograms, also known as hue histograms, are a statistical tools used to present frequency of colours in an image. If the image data was analogue, extracting colour, i.e. angular components of the ordered n-tuples of the recorded colour channels in the colour space, would be trivial. This is, however, not the case when dealing with digital image data. Even for a simple transformation from the RGB colour model to hue-saturation-lightness or luminance-chrominance colour space, the hue or chrominance component is either not accurate or not possible to calculate.

Therefore it is considered as necessary to discard pixels with large and small intensities as their saturation and hue, or chromaticity, components tend to be unstable [3, 4]. To conclude, when performing colour based pixels classification it is common to ad-hoc threshold values close to the achromatic axes before the actual colour histogram is generated which involves at least one additional parameter that needs to be predetermined.

We propose a method that overcomes this problem by taking into account uncertainty associated with each intensity determination, which is at least as large as half the step in the digital intensity values.

2. Method description in the two-colour case

When analysing colours, i.e., spectral components, of an image, it is common to define one or several predetermined wavelength intervals, within which intensity is determined. If a complete spectrum is of interest, the wavelength intervals are typically selected border to border, in order to cover the entire range.
Figure 1. Scatterplot illustrating the principle of compensation for quantization noise in two-colour images.

However, in other applications, the most relevant wavelength regions are selected, neglecting any information in other regions. The result in any of these cases is that every pixel is associated with at least two values representing intensity within a respective wavelength interval, i.e. a pixel vector \( p_i \). In other words, each pixel vector \( p_i \) is an n-tuple of intensity elements \( p_{i,k} \) where each component is associated with a pixel. Since the image is digital, the intensity elements \( p_{i,k} \) are thus digital values representing a discretized intensity measure of light, within a predetermined wavelength interval \( k \).

When recording photographic images, three wavelength intervals associated with blue, green and red are taken. Nevertheless, the proposed method will for simplicity be explained by a two-colour example, i.e., with two colour channels, and could be generalized to higher spectral dimensions straightforwardly.

In the two-colour case, the idea behind colour based pixel classification is reduction of dimensionality of the data, which can be yielded by transforming an input image into a 1D histogram. If the axes of two colour channels are selected to be perpendicular, the two-dimensional colour space corresponds to a conventional scatterplot. It is assumed that the pixels with zero of the second vector element corresponds to an angle of 0° and the pixels with zero on the first vector element corresponds to an angle of 90° as shown in Fig. 1.

2.1. Compensation for uncertainty of digital intensity values

Since the number of bins is chosen to be relatively large, one square in the scatterplot will cross into more than one bin range. The contribution from the square should be divided or smeared between the bin ranges crossing the square as shown in Fig. 1. This is particularly important for vectors having a small total intensity, since they tend to cover a larger angle range. If there is no additional information about any probability distribution within each square the contribution to each bin should be proportional to the area portion of the square that the bin range covers. Pixel \( p_i = (p_{i,1}, p_{i,2}) \) is distributed among all angles varying from the angle representing the bottom-right corner of the square representing \( p_i \) to the angle representing top-left corner. This means that the contribution \( c_{ij} \) to bin \( j \) should be distributed to all angles from a sufficiently small neighbourhood of \( \arctan(p_{i,2} + \frac{1}{2})/p_{i,1} - \frac{1}{2} \) to a sufficiently small neighbourhood of \( \arctan(p_{i,2} - \frac{1}{2})/p_{i,1} + \frac{1}{2} \). The contributions \( c_{ij} \) are pre-calculated and stored in an adequate look-up table for easy retrieval. For multispectral data the number of bins crossing the quantization uncertainty hypercube should be counted thus providing a dimension reduction from \( nD \) spectral data, to \( (n-1)D \) solid angle.

2.2. Weighting

As creation of a colour histogram reduces dimensionality of the data, weighting of all pixels can be used to emphasize other important pixel properties. For instance, in fluorescence microscopy it is important to avoid a large impact from pixels having a low intensity, i.e. typically dark background pixels, so the contribution from each pixel to the colour histogram is weighted by a factor that is a function of the length of the corresponding pixel vector in order to emphasize pixels with high intensities. The Chebyshev metric is preferred as the square shape of the first quadrant of a Cartesian coordinate system satisfies the idea that all angles between 0° and 90° should be represented equally [5].

The total value associated with bin \( j \) if both distance weighting and compensation for uncertainty of digital intensity values is employed, then becomes equal to the sum of products of \( |p_i| \) and \( c_{ij} \) for all pixel vectors \( p_i \) in the image. Since the scope of the paper is introducing a transformation from raw image data to a colour histogram, different approaches for multilevel histogram segmentation are not discussed. The appropriate method is usually depended on the particular image data.

3. Applications

3.1. Cross-talk suppression in microscopy

Cross-talk, or bleed-through, is the incomplete separation of fluorescence emission from different
flourochromes at image capture. Fluorescence emission, intended to be associated with a particular wavelength, may therefore give rise to detected intensities also at other wavelengths. This can be caused either by fluorescence emission spectra having components outside the main intended wavelength range and/or by incomplete spectral separation of the different detected wavelengths. The effect is proportional to the intensity of the signal. Stable methods for suppression of cross-talk are dependent on image capturing techniques and hardware settings. Hardware solutions for avoiding cross-talk are typically expensive and have to be adapted to the specific image capturing apparatuses.

In the image analysis based method, an input image is transformed into a colour histogram. By expressing the pixel vectors as linear combinations \([6]\) of the smallest, \(\alpha_{R}\), and the largest, \(\alpha_{G}\), dominating angles of the colour histogram, an image compensated for cross-talk can be produced. To illustrate the method cross-talk is simulated by adding the red channel \((p_{11})\) multiplied by a factor representing the degree of cross-talk to the green channel \((p_{12})\) of an image and adding Gaussian white noise. If we examine the colour histogram (Fig.2A) of a series of red, colocalized and green objects as shown in Fig.2B, one can see that the dominating angle of the “pure” colours is not situated in immediate vicinity of 0° and 90°; the red peak has been shifted from 0° to 32° due to cross-talk. Cross-talk to the red channel is significantly smaller since the green peak is shifted from 90° to 84°. This means that a pixel showing only “red” emitted light also contributes to the “green” intensity and vice versa. Images free of cross-talk are produced by making the correct linear combination of the original channels. As can be seen in Fig.2C, the proposed method has
resulted in suppression of cross-talk while preserving true colocalization.

It is also possible to suppress autofluorescence in microscopy images by using the colour histogram to generate fuzzy classification rules either for true signal amplification and background suppression or extraction of spectral unmixing parameters [7].

3.2. Skin detection

Color based segmentation for face detection or tracking applications is computationally less expensive while being relatively robust to changes in viewpoint, scale and scene illumination. The first classification step in this method is identifying skin regions by colour based pixel classification [8].

As said before, RGB colour space is not convenient for dimensionality reduction for colour based classification, and HSI colour space could contain many singularities. Therefore, luminance-chrominance colour spaces are a natural choice with \( L^*a^*b^* \) colour space being less preferred for this type of analysis, though it could be useful for visualization purposes. The \( Y'UV \) colour space fulfills several prerequisites – it can be one-to-one transformed to RGB colour space, it has the desired quadratic shape of the UV plane, and it is still commonly used in multimedia together with its derivative luminance-chrominance colour spaces.

The color of the human skin results from mixing the red color of the blood with the yellow or brown color of the melanin for all human races. More precisely the spectral analysis shows that the skin chrominance is confined into a zone in UV plane while the luminance \( Y' \) mainly reflects the lighting changes. This range corresponds to the interval 103° (red) to 167° (yellow) in UV-plane [9].

We propose an additional step for detection of pixels belonging to human skin based on analysis of a colour histogram in the second quadrant of the UV plane (i.e., 90° to 180°). Instead of applying fixed classification rules, new angle intervals are extracted based on statistics of the colour histogram.

To create the histogram, all pixels are weighted by one for any intensity and saturation value as they are all considered equally important. Naturally, pixels close to \( Y' \) axis are scattered over a range of bins as described in Section 2 while pixels being completely black or white lay on the achromatic axis \( Y' (U=V=0) \) and therefore have no effect on the colour histogram. The result of the extended pixel classification is compared to the original method in Fig. 3. The method is particularly useful for exclusion of regions identified as lips, eyes and hair without any texture analysis which is useful for further steps in face recognition.

4. Discussion

Having a significant number of saturated pixels affects the transformation since colour or spectral angle of saturated pixel vector is undefined. Enhancing contrast and brightness can also lead to errors, e.g., if digital intensity values are ranging from 0 to 63, simple multiplication by 4 would expand the range, but not the uncertainty interval each value has.

Complexity of creation of look-up tables is generally very high depending on the number of intensity levels. On the other hand, the complexity of our method is only a multiplicative of the number of intensity levels as compared to creation of a simple uncompensated colour histogram. That is more than satisfactory for large image data.

Since the proposed classification is pixel-wise, the number of spatial dimensions does not affect the method. In the case of dual-colour images, hue based classification is equivalent to classification based on spectral angle.

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References