COLOUR APPEARANCE DESCRIPTORS FOR IMAGE BROWSING AND RETRIEVAL

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ABSTRACT

In this paper, we focus on the development of whole-scene colour appearance descriptors for classification to be used in browsing applications. The descriptors can classify a whole-scene image into various categories of semantically-based colour appearance. Colour appearance is an important feature and has been extensively used in image-analysis, retrieval and classification. By using pre-existing global CIELAB colour histograms, firstly, we try to develop metrics for whole-scene colour appearance: "colour strength", "high/low lightness" and "multicoloured". Secondly we propose methods using these metrics either alone or combined to classify whole-scene images into five categories of appearance: *strong, pastel, dark, pale and multicoloured*. Experiments show positive results and that the global colour histogram is actually useful and can be used for whole-scene colour appearance classification. We have also conducted a small-scale human evaluation test on whole-scene colour appearance. The results show, with suitable threshold settings, the proposed methods can describe the whole-scene colour appearance of images close to human classification. The descriptors were tested on thousands of images from various scenes: paintings, natural scenes, objects, photographs and documents. The colour appearance classifications are being integrated into an image browsing system which allows them to also be used to refine browsing.

Keywords – Colour appearance attribute metrics, colour appearance descriptor, image retrieval and browsing

1.0 INTRODUCTION

A well known problem in content-based image retrieval systems is to rank results in a meaningful way from the point of view of human perception. The appearance of a colour can be reasoned about fairly well using perceptually-based colour spaces such as CIELAB. While our earlier research concentrated on making various image descriptors such as colour histograms, PWT, CCV etc[1], it was clear that a heuristic approach to associate descriptors with meaningful classes would be fruitful. So while it is possible to compare two colour histograms to compute a similarity between then there are many different visual aspects which can be explored. It also seems that direct access to image pixels may not be possible after low level image descriptors have been produced from a massive web-crawl for example (where the original images are not kept). It is also possible that collections would prefer to release only the image descriptors. So we have concentrated here on making useful visual appearance associations purely from one image descriptor as a test case, where plenty of knowledge about human perception exists: the colour histogram.

Classification can help users to search and browse large-scale image databases by hierarchically grouping images into categories which the user understands. Many researchers are currently working on how to bridge the *semantic gap* between the computer's interpretation of image data and human semantics[1, 2, 3, 4, 5, 6]. Colour is the most distinguishing feature that is easily perceived by humans and has been extensively used in image-analysis, retrieval and classification. Hence, browsing thousands of images can be made easier with an appropriate colour descriptor. Typical examples of complex queries are - find me objects or paintings which have many strong colours; search for any 20th Century sepia photographs; look for vases or carpets with a design which has pastel colours. This paper presents algorithms which use the CIELAB colour space histogram and its appearance attributes to produce appearance classes/rankings. Three metrics have been developed and five methods have been proposed to classify the whole-scene appearance of images as strong, pastel, pale, dark and multicoloured.

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2.0 RELATED WORK

There are two general approaches to associating colour-based semantics to images. The first approach is based on the relationship of the chromatic colours in the image. In this approach, image features taken either from the entire image or from specific regions are compared in terms of chromatic similarity. In the second approach, image retrieval is based on the appearance of the image considering the relationships between existing colours. In this approach, the appearance of the image can only be noticed when the content of the image or part of image is observed as one whole entity.

Much of the research work uses the first approach and many were carried out on artwork. QBIC[7] and PICASSO[8] are two examples of colour-based image retrieval systems developed for this purpose. QBIC supports syntactic colour searches on dominant colour and colour layout search e.g. red and dark blue. On the other hand, PICASSO supports semantic queries such as the contrast of pure colours, warm-cold, light-dark, and unsaturated-saturated; and harmony-based e.g those colours which become grey in combination. Some examples of harmony-based images can be found in Jose and Guan.[9]. In PICASSO, the search on the images could be done on whole images as well as some inter-region colour relationships.

For the second approach, to our knowledge, there is still not much research done to describe the appearance of images. Mojsilovic[10] proposed a method based on colour composition of images to describe an image as dark, pale, monochromatic or having vivid colours. In their work, they started with colour-segmentation of the image. Then by using their own vocabulary and syntax developed through subjective experiments, they attached colour names to all pixels labelled as uniform or texture. Then the histogram of colour names was computed to generate the description of the colour composition.

2.1 Colour Histogram

A colour histogram which captures a global colour distribution in an image is the most widely used colour descriptor. It is often combined with other descriptors such as shape and texture to produce classifications. Szummer and Picard[11] proposed a method for distinguishing between indoors/outdoors using a colour histogram, autoregressive texture model and discrete cosine transform information. Swain et al.[12] described how to classify photographs from computer-generated images on the web based on colour metrics. Vailaya et al.[13, 14, 15] described a method to classify vacation images between landscape/city, indoors/outdoors, and sunset/mountain/forest scene by performing two class discrimination using colour histograms, colour coherence vector (CCV), DCT coefficients, edge histogram and edge direction coherence vector. Lienhart and Hartman[16] and Florin Cutzu et el.[17] also used colour in their classifications.

2.2 CIELAB Colour Space and Colour Appearance Attributes

CIELAB is a convenient and relatively perceptually uniform colour model developed based on human perception. It is also easy to compute perceptual attributes such as lightness, hue and chroma. By using the definition given by the CIE, saturation can be expressed as:

$$\text{Saturation (S)} = \text{chroma } (C^*) \,/\, \text{lightness } (L^*) \tag{1}$$

However, the saturation measurement using this formula gives a high saturation for dark areas, although to the eye these can not be seen so easily. Hence we propose a modification to the equation to obtain to measure which can describe the fact that dark colours are not perceived as saturated.

2.3 CIELAB Colour Histogram

In this work, the CIELAB colour histograms were generated using software (FVS: Feature Vector Software) originally designed in the Artiste[1] project which has been further developed in the SCULPTEUR[18] and eCHASE projects. A set of around 12 image descriptors are maintained for around 50,000 images from museums involved in the projects. FVS was developed in a Unix environment using VIPS functions, a free image processing system widely used in arts applications[19]. The CIELAB histogram uses a 3D binned space (Figure 1) where each bin is the proportion of pixels in the bin's colour range. In the experiment, we set the dimension, n = 15 for each of the L*, a*, and b* axes. This makes the colour difference between each bin significantly different (around 6-15 JND's).

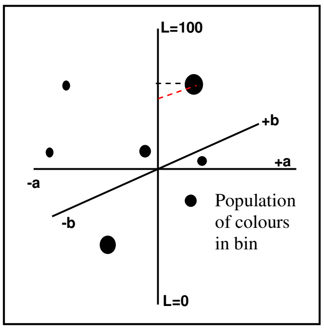


Figure 1 : CIELAB Colour Histogram

The aim was to derive "colour strength" metric, "high/low lightness" metric and "multicoloured" metric from this histogram. The definition of the histogram and metrics are as follows.

2.4 Definition of Histogram

1. H_{lab} . is a CIELAB 3D histogram.
2. n is the number of dimensions per colour channel for L*, a* and b*. We set n = 15.
3. N is the number of bins in histogram H_{lab}. $N=n^3$.
4. CR_{ab} and CR_{lab} is the vector for a bin in the histogram.
5. CR_{ab} is part of CR_{lab} and CRl_{ab} is part of H_{lab} therefore $CR_{ab} \in CR_{lab} \in H_{lab}$.
6. $CR_{lab} = l_i,a_j,b_k$ i,j,k = 0,1,2………n-1.
7. $CR_{ab} = a_j,b_k$ j,k = 0,1,2………n-1.
8. V_{lab} is the proportion of colours in the image corresponding to LAB bins, this value has been normalized 0 to 1.
9. $V_{lab} = l_i,a_j,b_k$ i,j,k = 0,1,2……..n-1.
10. C^*_{ab} is the chroma for CR_{ab} , where , CR_{ab} are the bins in a*b* plane.
11. TD = Threshold for dark light where saturation is undefined.

3. METHODOLOGY : COLOUR APPEARANCE DESCRIPTORS

The whole-scene colour appearance of an image can be described as *strong*, *pastel*, *pale*, *dark*, *monocoloured: greyscale* and *multicoloured*. The names of these classes are based on those commonly used by people to describe pictures. An image is described as *strong* if its whole-scene colour appearance is perceived as *vivid* and highly saturated. *Pastel* images appear to have *soft* colours, ie light or less *strong* colours. A *pale* image will be perceived as *dull*, *diluted*, *weak* or more greyish or whitish in colour. On the other hand, a *dark* image will appear generally darker. *Multicoloured* images can be described as those with several different colours which are perceived separately and noticeably. *Greyscale* images are another well known description, while *sepia tone* is one specifically known for old photographic prints. In this paper, our definition of *multicoloured* images is they should have at least three different significant hues at certain level of proportion.

Strong and *pastel* appearances can be determined from the "colour strength" metric and *pale* appearance can be determined using "colour strength" and "high-lightness" metric. *Dark* appearance can be identified using a "low-lightness" metric. In the next section the computation of the "colour strength" and "high/low lightness" metrics are explained, followed by the methods for *strong, pastel, pale* and *dark* appearance descriptors. Finally the "multicoloured" metric calculation and descriptors are discussed.

3.1 "Colour Strength" Metrics Calculation

3.1.1 "Colour Strength" Framework

We define "colour strength" metric based on the saturation definition. It is quite straightforward to measure colour appearance attributes i.e saturation and colourfulness of an individual patch of uniform colour stimulus. However, to measure the colour appearance of a multicoloured stimulus for example (paintings, natural scene, indoor scene) is a more difficult task. Generally, researchers use statistical parameters i.e mean, standard deviation etc. to compute appearance attributes of whole images[20, 21, 22].

Saturation can be defined as relative colourfulness and to approximate overall saturation of an image, equation (1) is used. However, according this equation, at a constant chroma C^* i.e. S is maximum when L is smallest and S is minimum when L is highest. This indicates that for a low level of lightness (very dark), the saturation will be high. Some results where lightness is very low will distort the perceived saturation by humans. An image that has dark chromatic colours will only appear dark from the human point of view. Neither chroma nor saturation provide a good relationship to how "strong" a colour is perceived.

On the other hand, a saturation decrement is more noticeable at medium to high lightness. Juan and Luo[23] in their paper, point out that in very dark stimuli which are close to the black point, saturation is a difficult attribute to estimate accurately. They conducted psychophysical experiments and the results show that saturation is closely associated with lightness and colourfulness attributes, where an increase in saturation will increase colourfulness but with a reduction of lightness. Henryk Palus[24] has shown that colourfulness is reduced in both directions of lightness away from the mid-point. In his research, he also observed the relationship between the colourfulness and the saturation of images where increments in colourfulness will also increase the saturation.

Using findings from[23] and[24], a list of definitions have been proposed in our attempt to develop "colour strength" metrics according to human perception research. They are as follows:

1. If there is a reduction in colourfulness, that will also reduce the saturation of an image.
2. Colourfulness is reduced in both directions of lightness away from the mid-level of lightness. The reduction is assumed to be uniform.
3. Saturation is defined as zero for very low lightness.

Based on these definitions, we define the *Saturation* of whole-scene images as *Defined Saturation* (*DS*) and *Undefined Saturation* (*UDS*). *DS* is calculated when Lightness $L_i > L_{TD}$ and $L_i < 100$. *DS* is maximum if $L_{i=50}$ and *DS* will be reduced if L_i reduces/increases in both directions from the mid-point, where $50 < i < 100$ and $TD < i < 50$. *UDS* exist when *Lightness* $L_i < L_{TD}$ where $0 < i < TD$. All colours which are defined as *UDS* are set to have zero saturation. Clearly for the neutral colours - black, white and greys, the saturation is zero because the chroma is zero.

In this method, the overall saturation of an image is calculated based on its defined saturation. The bins with colours which were perceived as dark were set to zero for their local saturation. This can be described in the following equation:

$$\text{Overall Saturation } (SAT) = DS + UDS \tag{2}$$

$$\text{Undefined Saturation } (UDS) = 0 \tag{3}$$

$$\text{Lightness } (L^*) = L^*_{mid} + \| L^*_{mid} - L^* \| \tag{4}$$

$$\text{Defined Saturation } (DS) = C^*/L^* \tag{5}$$

By simplifying (2), (3), (4) and (5), the overall saturation, *SAT* for an image can be computed as:

$$SAT = \frac{C^*}{\left(L^*_{mid} + \left\| L^*_{mid} - L^*_i \right\|\right)} \quad \forall i = TD..100 \tag{6}$$

Where $mid = 50$, *TD* is the *Lightness* threshold where saturation for chromatic colours below this lightness is undefined.

In general, the overall saturation is measured by calculating the purity of chroma in each bin relative to its condition of lightness. This can be calculated by first finding the local saturation for each by dividing the local chroma by its lightness and normalizing the value. Secondly, finding the area of each bin. Thirdly, calculating the overall saturation by finding the summation of local saturation. This overall saturation is normalized (0:desaturated to 1:saturated). Equation (6) is the modified equation proposed for the saturation measurement used in this work.

3.1.2 "Colour Strength" Metric Calculation

1. $C^*_{ab} = ((a^*)^2+(b^*)^2)^{1/2}$, where a^* and b^* are the mid point of the bin .

2. For each relative lightness and chroma, the local saturation for each bin, LS_{ab} can be computed as:

$$LS_{ab} = \sum_{a=0}^{A}\sum_{b=0}^{B} C^*(a^*,b^*)/L^* \qquad \forall L^* = TD..n-1 \quad \forall a,b = 0..n-1$$

Normalize the local saturation, S_{max} when $L^*= L_{50}$ and S_{min}. when $L^* = L_{TD}$.
Find the area, AS_{ab} of each bin. This can be computed as

$$AS_{ab} = \sum_{a=0}^{A}\sum_{b=0}^{B} V(a,b)*LS(a,b) \qquad \forall a,b = 0..n-1$$

3. Therefore , overall saturation, SAT can be computed as the summation AS_{ab} as below:

$$SAT = \sum_{a=0}^{A}\sum_{b=0}^{B} AS(a,b) \qquad \forall a,b = 0..n-1$$

SAT is a whole-scene "colour strength" measurement value between 0 (desaturated) to 1 (highly saturated).

3.2 Lightness Metric Calculation

3.2.1 Lightness Framework

The lightness of an image is measured by examining the luminous intensity of colours of the whole content. Two calculations for lightness metric are used to reflect low luminance and high luminance. L* is split into three ranges: Low, Medium and High as shown in Figure 2. The populations from bins located in low and high lightness areas are accumulated. All the values in the bins of the histogram are analyzed and accumulated according to the lightness intensity levels. For a dark appearance, we look for colours which have low lightness intensity and for the pale appearance the colours with high lightness intensity are examined.

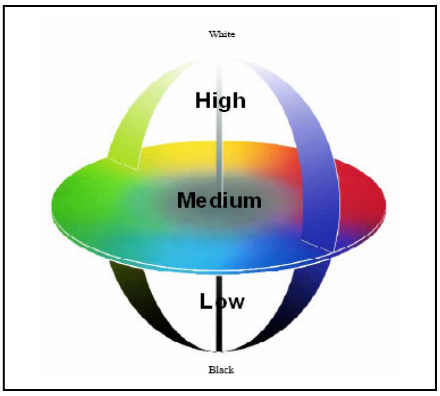


Figure 2: Three lightness intensity level

3.2.2 Low-Lightness Calculation

From the CIELAB 3D histogram H_{lab} , low illumination for the whole-scene, *LOW* can be calculated as

$$LOW = \sum_{a=0}^{A}\sum_{b=0}^{B} V(a,b), \forall l = 0..llow \qquad llow \text{ is threshold for low lightness}$$

Dark appearance images can be detected from a low lightness metric. High values of this metric shows the image is a dark scene. In this method, *llow* = 4. Dark appearance images were those which have low-lightness value > 0.9.

3.2.3 High-Lightness Calculation

From the CIELAB histogram H_{lab}, high lightness for the scene, *HIGH* can be calculated as

$$HIGH = \sum_{a=0}^{A}\sum_{b=0}^{B} V(a,b), \forall l = lhigh..n-1 \qquad lhigh \text{ is threshold for high-lightness}$$

3.3 Strong, Pastel and Pale Appearance Descriptors

"colour strength" and lightness metrics have been derived for 337 training images with various scenes selected randomly from the National Gallery and Victoria and Albert Museum collections. The "colour strength" metrics were then sorted from high to low values. From the sorted list, 10 values have been selected and Ranked. Figure 3a shows 10 images ranked from highest to lowest based on their "colour strength" values. The "colour strength" metric derived from the proposed calculation method shows a gradually change from *strong* to *deep* to *pastel* and finally to *dull* appearance which is more whitish/greyish/blackish.

These flow of changes of the appearance can be seen almost equivalent to the results obtained from human evaluation test towards "colour strength" ranking as shown in Figure 3b. There is a strong agreement for the top and bottom ranking. There are more subjective observations slightly towards middle ranking (highlighted images) which should only slightly affect the overall ranking. Using this outcome, *strong, pastel* and *pale* appearance descriptors were developed. The methods have been tested using our system containing more than 16,000 colour images with various scenes – paintings, natural scenes, indoor/outdoor.

Strong and *pastel* appearance can be determined from the "colour strength" metric. Figure 4 and 5 shows *strong* and *pastel* images obtained from the proposed *strong* and *pastel* descriptors. *Pale* appearance images can be identified using a scaling from "colour strength" and high-lightness metric . Figure 6 shows *pale* images obtained from the proposed *pale* descriptors. *Dark* appearance images can be identified using low-lightness metric. Figure 7 shows *dark* images obtained from the proposed *dark* descriptors.

highest

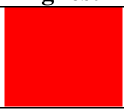
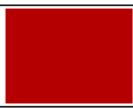
Image					
Metric	0.877193	0.558038	0.494037	0.233314	0.182782

Image					
Metric	0.0845497	0.0662362	0.0596624	0.0332497	0

Figure 3a : 10 images ranked from the highest to the lowest values by "colour strength" metric

highest

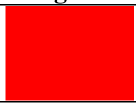
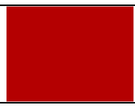
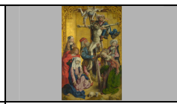
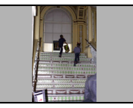
Image					
Metric	0.877193	0.558038	0.494037	0.233314	0.182782

Image					
Metric	0.0845497	0.0662362	0.0596624	0.0332497	0

lowest

Figure 3b : 10 images ranked from the highest to the lowest values by humans

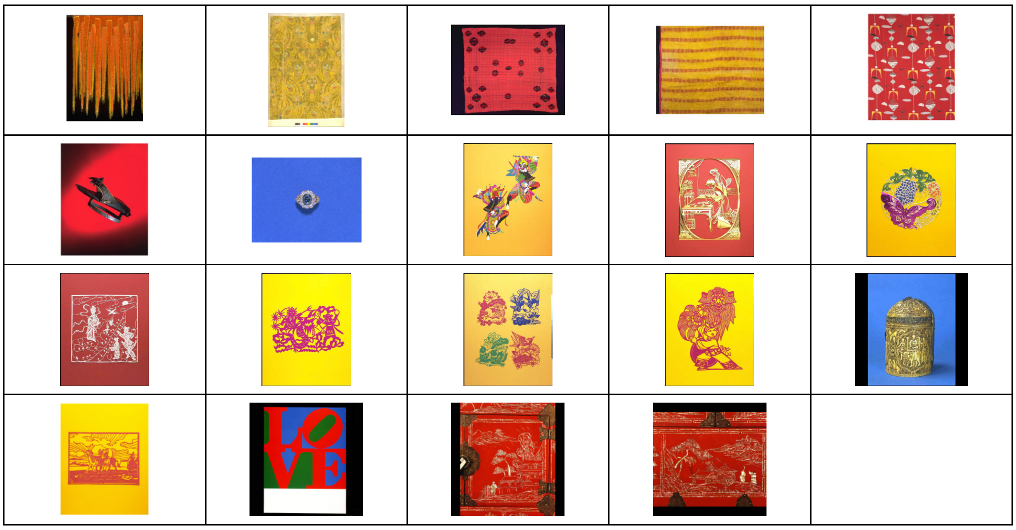


Figure 4 : "Strong colour" Images

Figure 5 : Pastel images

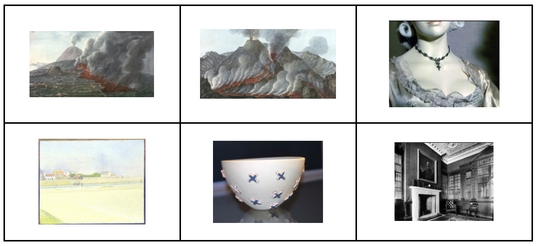


Figure 6: Pale images.

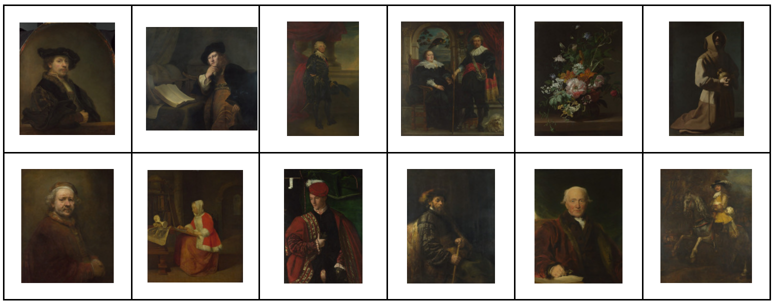


Figure 7 : Dark Images

3.4 Multicoloured Metric Calculation

The Multicoloured metric was developed to determine multicoloured appearance. The algorithm also classifies monocoloured, greyscale and sepia tone images. To our knowledge, there is little existing work to detect multicoloured images or the "multicolouredness" of an image. In this paper, we discuss only multicoloured appearance. Monocoloured for greyscale and sepia are the subject of current research.

3.4.1 Multicoloured Framework

Visual attributes that are related to the calculation of this metric are hue and chroma. *Chroma* C^* is calculated based on two colours value a^* and b^* and hue is detected by hue angle H_{ab} . In our multicoloured appearance determination, colour names are not involved. The number of unique hues which exist in the image content are taken into account, their chroma levels as well as the proportions. Based on CIELAB hue angle from Hung and Berns[25] and adjusted blue angle in Braun and Fairchild[26], six unique hues with their range of angle (0°-360°) have been defined. Hues are labelled as *C1, C2, C3, C4, C5* and *C6*. The approximate angle associated with these hues are as follows: *C1*: 0° – 59°, *C2* : 60° – 119°, *C3* : 120° – 179°, *C4* : 180° – 259°, *C5* : 260° – 299° and *C6* : 300° – 359° as illustrated in Figure 8. For chroma levels, we used the same values as in Kelly and Judd[27] as well as for saturation: Greyish, Moderate, Strong and Vivid.

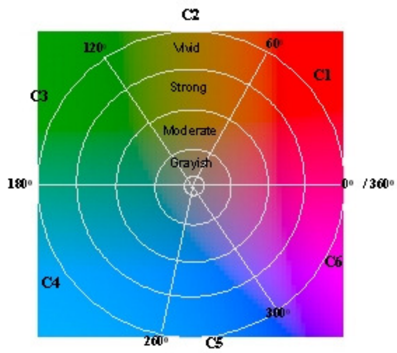


Figure 8: 2D AB plan view showing six unique hues, their hue angles and the four levels of chroma intensity.

For each image, its colour histogram is analysed to gain all information regarding its hues and chroma level. It is essential calculate the chroma intensity of each hue to detect multicoloured images. A certain proportion of bright colours in the whole-image content is required to give a perceptible multicoloured appearance. A multicoloured metric for an image can be obtained as follows: first, its hue metric is obtained by determining and counting all non-zero bins in the histogram, accumulated according to their level of chroma. Secondly, for any three hues, the proportion for each hue and their combination were examined. Both values are used to determine the multicolouredness of images. The pseudo code for this method is shown here.

3.4.2 Calculation Method

```
BEGIN
   If bins are in sepia range
           Accumulate into sepiacolour
   If bins are in grey colours
           Accumulate into greycolour
    For C_{i=1} to C_{i=6}
      BEGIN
           {Find number of bins for each level of chroma }
                  VH       = Total Bins of Ci_vivid
                  SH       = Total Bins of Ci_strong
                  MH       = Total Bins of Ci_Moderate
                  GH       = Total Bins of Ci_grayish
           MM = Weight[GH|MH|SH|VH]
           IF (GH >= n1 && MH>= n2 && SH>= n3 && VH>= n4 )
              Begin
                 If (The proportion of each of any three hues, Cx, Cy, Cz > T1) &&
                    (the proportion of combination of the same hues, Cx, Cy, Cz > T2 )
                     image = multicoloured big patches
                 else
                     image = multicoloured small patches
              End
           ELSE
              image =less multicolour
      END
      If sepiacolour > ths
         Image = sepia
      If greycolour > thg
         Image = grey

END
```

From the above pseudocode, *sepiacolour* is a variable that measures the amount of sepia colour in the image and *ths* is the threshold for sepia tone appearance. *greycolour* is a variable that measures the amount of grey colour in the image and *thg* is the threshold for greyscale appearance. *n1, n2, n3* and *n4* are the thresholds for the number of colours for each chroma level. C_x, C_y, and C_z are any three unique hues, where x, y, and z are in the range of 1 to 6. *T1* and *T2* are the thresholds for the amount of proportion for each existing hues and combination of all hues. In this test, *ths* = 0.999, *n1* = 5, *n2* = 3, *n3* = 1, *n4* = 0, *T1* = 0.08 and *T2* = 0.5. These values are determined as potential thresholds after running numerous experiments on a set of images and comparing the results. Multicoloured Metric, *MM* can be weighted as *[GH,MH,SH,VH]*.

For example if an image has *VH* = 2, *SH* = 4, *MH* = 6, *GH* = 5, the multicoloured metric for that image is *MM* = [5,6,4,2]. However, from the observation of the sample results, because of *VH* range is very rare in typical image content, we combine it with *SH*. Thus, MM = [GH,MH,SH+VH]

Figure 9 shows some images with their MM values. All the top images appear multicoloured. We plan to do further research to tune the characteristics of the MM values.

6610 666 664 664 642 632 543 534

Figure 9: Multicoloured images showing their MM values

3.5 Multicoloured Appearance Descriptors

Each bin counts the proportion of pixels with colour within a certain range and each bin has a single representative hue. For the determination of multicoloured images, the proposed method is based on two rules as follows:

1. The chroma level of related hues are above thresholds and
2. The existence of these hues, with the amount of each of them and their combinations are above the thresholds,

If both conditions are fulfilled, images will be classified as multicoloured images. If only the first condition is fulfilled, images are classified as multicoloured images (typically these have small colour patches). If both conditions are not fulfilled, images are less multicoloured or monocoloured. From our experiments, a multicoloured image could also appear pastel or strong. Figure 10 shows sample multicoloured images and illustrates the nature of the algorithm. It can be seen that the lack of spatial analysis in these algorithms leads to images with many small colour areas (ie textures) having the same metrics as those with large uniform colours.

Figure 10 : Multicoloured Images

4. CONCLUSION

We have developed methods to classify images according to the colour appearance descriptions which humans understand. In the future this will allow people to find images more easily. Overall, the metrics developed using solely the CIELAB colour histogram, to mark-up images with appearance concepts show positive results. A “colour strength” metric can be used to classify the colour appearance as strong, pastel and pale when scaling together with the High-lightness metric. The Low-Lightness metric can identify dark images and the multicoloured metric can be used to identify multicoloured and monocoloured: greyscale and sepia tone images.

The results from our proposed methods show that this is a contribution to bridging the semantic gap in the area of whole-scene colour appearance. Initial small-scale human observation tests have been carried out and extensive tests planned for the future developments. Subjective trials are important to determine not only the quality of the algorithms but to develop thresholds for classifications.

These colour appearance classifications are being integrated into an image browsing system which allows them to also be used to refine browsing. In some application, for instance, in the digital library of items collection, these descriptors, can be combined with metadata. For example, in browsing certain collections e.g. multicoloured vase or rugs with bright and vivid colours, or to search for some water-colour paintings. These descriptors can therefore help the searching process. Finally, in the future, we plan to use these descriptors together with segmentation, with the aim that the analysis will take into account the spatial layout of the colour.

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