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articles

Influence of Background on the Colour Appearance of Images

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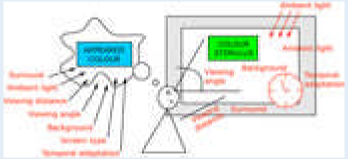
Summary

In this paper we have investigated whether colour perception is affected by the distribution and the spatial organisation of colours in a complex image. In the first part of our study, we analysed the influence of scene content and of background types on the colour appearance judgement. To reach this aim we ran visual assessment experiments based on the magnitude estimation technique and we investigated various visual phenomena, such as brightness adaptation, chromatic spatial adaptation, contrast effects due to sizes and coloured backgrounds, display field sizes and dynamic range in the scene. The examination of numerous visual assessment results done showed that the influence of the background on colour appearance is more noticeable for complex images with high frequencies than for colour images with low frequencies or simple images. Likewise, the influence of the background on colour appearance is more noticeable for chromatic images with a large gamut than for less coloured images with a low gamut. In the second part of our study, we analysed the influence of the local colour saliency on the colour appearance. We developed a computational model to measure colour contrast. Our motivation was to define an objective metric consistent with observer valuation. The proposed model integrates in a single model the influence of average colour perception and the interactions between local and global spatial structures according to the visual eccentricity. The measure of colour contrast relies on a set of parameters organised in a hierarchical structure. The computation is based on spatial criteria and integrates low-level factors calculated on defined regions relatively to their local and global neighbourhoods.

Introduction

Figures and Tables

Figure 1



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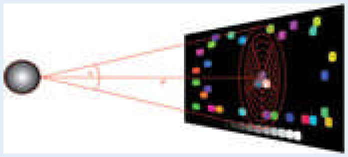

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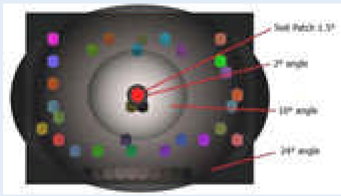

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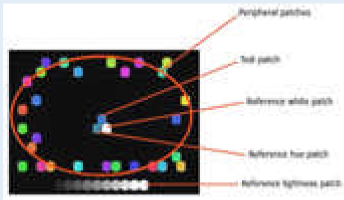
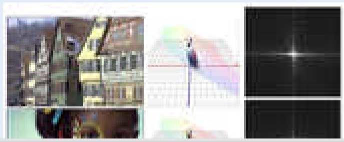


Figure 5



It is well known that colour appearance of a scene depends on the environment in which elements are viewed and that colour perception is affected by the distribution and the spatial organisation of colours [1]. During the last decade, increased knowledge about colour perception has been exploited in computer vision to improve colour management and to develop computational models which correlate with human perception. The fidelity of the correspondence between algorithmic predictions and human perception is important because it ensures the validity and the relevancy of objective measures compared with subjective valuations [2]. Colour appearance descriptors should play a major function in computer vision. It could be helpful to improve models with application in visual search, video compression, image database querying, and all other image processing fields where human observer is directly implied [3–4].

Colour appearance is influenced by several and different factors such as spatial colour distribution in the observed scene or spatial induction from different coloured surfaces. Surround and background largely influence the colour appearance of a patch. Previous works showed the importance of colour contrast in the judgement of perceived colours [1–2]. For example, Olzak et al. studied the centre-surround interactions between coloured areas in fine spatial discriminations [5]. Other works showed the importance of colour saliency in the perception of complex images [6]. One major drawback of most existing saliency models is that either colour information is not integrated in the computation or it is taken into account only through the raw RGB components of processed images [7]. For example, Van de Weijer *et al.* proposed a salient point detector based on the analysis of the statistics of colour derivatives of RGB components [8]. Another important drawback of current saliency models is that local spatial organisation of the visual scene generally does not play an active part in the processing. However, it is, for instance, well known that a large uniform patch does not attract visual attention as a fine textured structure does. Moreover, colour appearance is widely dependent on the local spatial arrangements. When a lot of papers deal with the detection of points of interest, few works study the extraction of Regions of Interest (ROI). However we can note that ROI detection based on visual attention mechanisms is increasingly discussed in the image processing community [9–14]. For example, Hu *et al.* propose a Visual Attention Region (VAR) process which involves the selection of features such as intensity, colour, orientation and size as performed by the primary visual cortex [15]. The uniqueness of a combination of such features at a location compared to its neighbourhood indicates a high salient region. The selection of ROI is directed by both neurological and cognitive resources. Neurological resources refer to bottom-up (stimuli-based) information when cognitive resources refer to top-down (task-dependent) cues [16]:

Figure 6

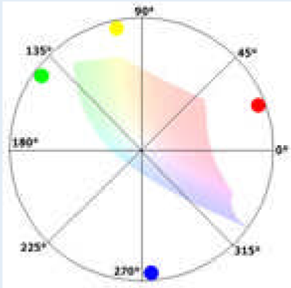


Figure 7

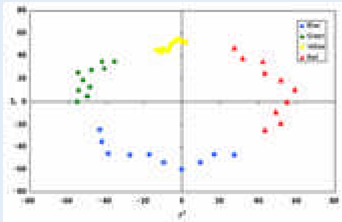


Figure 8

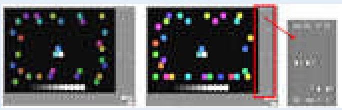


Figure 9

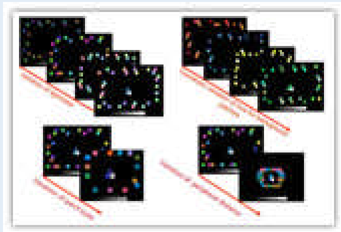


Figure 10

- Bottom-up information is controlled by low-level image features that stimulate achromatic and chromatic parallel pathways of the human visual system [17].
- Top-down cues are controlled by high-level cognitive strategies largely influenced by memory and task-oriented constraints [18].

It is well acknowledged that the visual field is decomposed into a set of ROI [19]. It means that visual attention mechanisms offer an effective approach to analyse complex scenes with limited transmission bandwidths and processing resources [20]. According to numerous studies, the future of visual attention models will follow the development of perceptual multiscale saliency map based on a competitive process between all bottom-up cues (colour, intensity, orientation, location, motion) [21–24]. In order to be consistent with human visual perception, colour information must be exploited on the basis of chromatic channel opponencies. Likewise, in order to be consistent with neural mechanisms, all features must be quantified in the LMS colour space. During the competitive process colour information must be modulated by local spatial arrangements of the visual scene.

One goal of the present work was to explore how complex spatial backgrounds influence colour appearance, without taking into account the implicit semantics of the image. We have therefore limited our experiments to the study of complex (natural) images segmented. We have not studied the influence of segmentation of colour appearance, as Wichmann [25] or Canosa [26] did. In general, to estimate the colour appearance of an ROI, the observer both focuses his attention on specific (segmented) areas of the background, and globally views the entire image [25]. In our study, we have not investigated whether the observer focuses his attention on specific (segmented) areas of the background; we have only taken into account his global judgement.

The aim of the first section is to give a brief state of the art of colour appearance models and visual appearance models in order to show how visual saliency parameters interact with colour appearance parameters.

The following section is devoted to analyse the influence of scene content (colour patches and spatially-varying images) and of background types (a simple chart with a few number of colour patches, complex spatial backgrounds and spatially-varying backgrounds) on the colour appearance judgement. To reach this aim we ran visual assessment experiments based on the magnitude estimation technique. This scaling technique was the key point of LUTCHI dataset experiments [27]. The aim of this study is not to provide absolute quantitative values, in such a case the colour matching technique would have been more accurate, but to evaluate

Figure 11

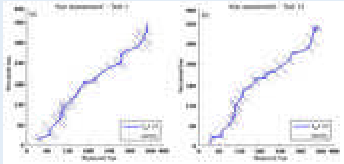
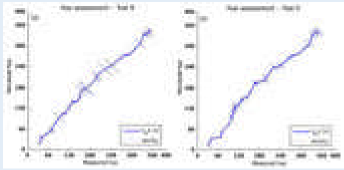


Figure 12



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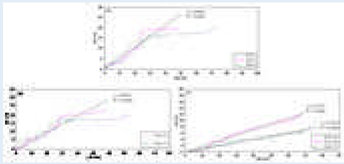
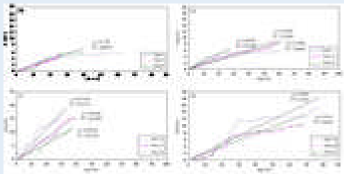


Figure 14



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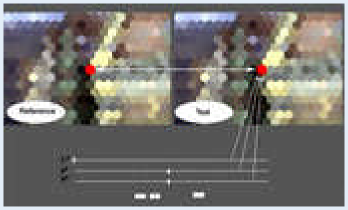
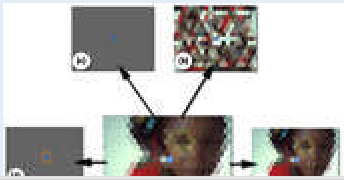


Figure 16



Moreover, Luo exposed three advantages of magnitude estimation [27]. It provides absolute perceptual values for colour attributes. It gives results perceptually equivalent to those predicted by colour appearance models easily leading to derive a colour model. Finally, it expresses colour in a consciously reportable form. In our study, we investigated various visual phenomena, such as brightness adaptation, chromatic spatial adaptation, contrast effects due to sizes and coloured backgrounds, display field sizes and dynamic range in the scene. A previous work was done by Webster [1], in which the motivation was to examine changes in colour perception resulting from adaptation or induction to colour contrast in spatially varying backgrounds. Our motivation was quite different; our aim was to examine background influences on colour appearance to define new specific viewing parameters consistent with colour perception. Another work was also done by Fairchild [28], in which the motivation was to propose an image appearance model referred to as iCAM. The iCAM model has a sound theoretical background; however, it is based on empirical modelling of viewing parameters relative to the image content, background and surround rather than a standardised colour appearance model such as the last referent CIE colour appearance model: the CIECAM02 [29]. Moreover, filters implemented are only spatial and cannot contribute to colour rendering improvements for mesopic conditions with high contrast ratios and for a large viewing field.

The third section is devoted to introduce a computational model developed to measure colour contrast. The idea is to define an objective metric consistent with observer valuation in order to test the influence of the local colour saliency on the colour appearance. The proposed approach integrates in a single model the influence of average colour perception and the interactions between local and global spatial structures according to the visual eccentricity. The measure of colour contrast relies on a set of parameters organised in a hierarchical structure. The computation is based on spatial criteria and integrates low-level factors calculated on defined regions relatively to their local and global neighbourhoods.

Colour Appearance Models

The first colour appearance model (CAM) recommended by the CIE in 1997 was CIECAM97s [30–32]. Next, in 2004, this model was superseded by the CIECAM02 in order to overcome several shortcomings [33–35]. CIECAM02 predicts satisfactory, within some limits, a wide range of perceptual factors contributing to colour image difference perception. Nevertheless, it insufficiently took into account some very important perceptual factors linked to: viewing conditions (surround and background, luminance range, luminance adaptation, chromatic adaptation);

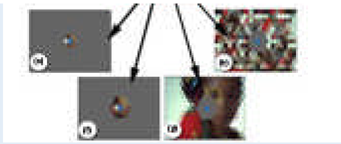


Figure 17

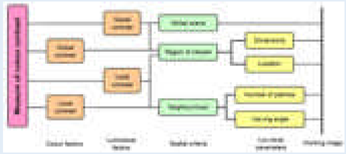


Figure 18

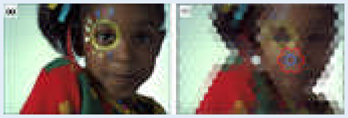


Figure 19

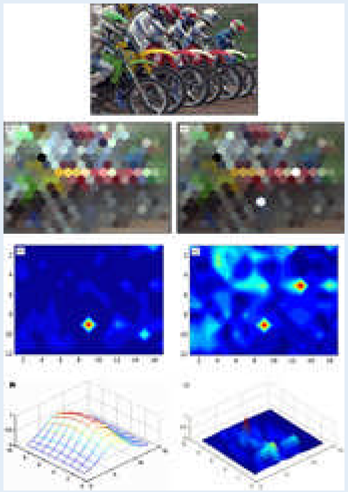


Figure 20

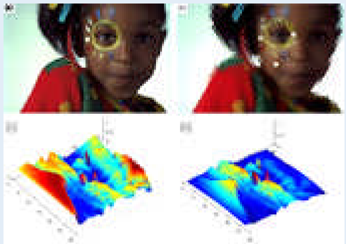


Figure 21

spatial effects (sample size, size of stimulus, contrast, spatial adaptation), and mesopic vision (rod contribution).

The main perceptual factor which influences colour appearance estimation is related to *viewing conditions*. In CIECAM02, viewing conditions are defined by the illumination (light source and luminance level) and by the luminance factors of background and surround (average, dim or dark). These parameters are very difficult to define, so they lead to confusion and deviations in experimentation. Recent work had been carried out to better predict changes in colour appearance with different viewing parameters [36–37]. The second perceptual factor which has a profound impact on the colour appearance is linked to the *luminance range* of the image observed (white-to-dark, e.g. from highlight to shadow) and more generally to the background surrounding the objects in the image. Such a hypothesis has been already reported by Hubel [38] and Corriea [39] with regard to the problem of assessing image quality using segmented contents. Likewise, Webster proved that colour perception changes in spatially-varying backgrounds [1]. To examine the effect of adaptation and induction to colour contrast, Webster used a hue-scaling task. The third perceptual factor which has a profound impact on the colour appearance of an image is linked to the state of *visual adaptation* of the observer. Most models of colour appearance assume photopic vision, and completely disregard the contribution from rods at low levels of luminance. The only colour appearance model which includes a rod contribution was the Hunt 1994 model [40]. Likewise, Kwak [37, 41] had investigated the problem of colour appearance under mesopic vision conditions using magnitude estimation technique.

The idea of this paper is not to improve the CIECAM02 model by incorporating perceptual factors such as those cited above but to compute the influence of these factors on colour differences perception. A complete model should predict various well-known visual phenomena such as the Stevens effect, Hunt effect, Bezold-Brücke effect, simultaneous contrast, crispening, colour constancy, colour memory, discounting-the-illuminant, light, dark and chromatic adaptation, surround effect, spatial and temporal visions. All these phenomena are caused by the change of viewing parameters, primarily illuminance level, field size, background, surround, viewing distance, spatial and temporal variations, viewing mode (illuminant, surface, reflecting, self-luminous or transparent), structure effect, shadow, transparency, neon-effect, saccades effect, stereo depth, etc (Figure 1). We have limited our scope to the *viewing conditions*, the *luminance range* and the *visual appearance*, because their influence is strong when an observer sees a digital image, particularly when an observer sees an image under mesopic viewing conditions.

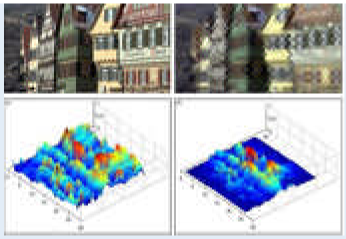


Figure 22

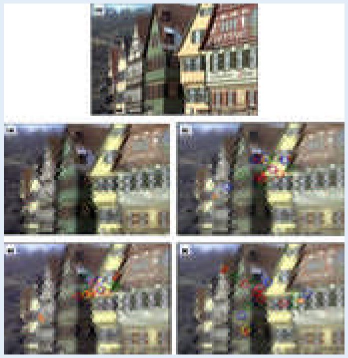


Figure 23

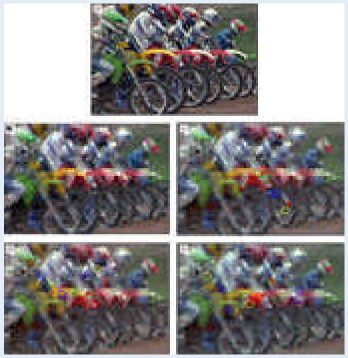


Table 1

Table 2

Over the last decade different computational models of attention have been introduced to provide a saliency map which codes the local visual attractors over the entire scene [26, 42–43]. We can suppose that visual attractors influence the colour appearance of an image and more specifically the colour saliency which codes the local regions where colour features such as hue, contrast, and opponency would guide the attention of a human observer during a visual search task over the entire visual scene [16, 44].

Sano has shown that the perception of colour difference is image dependent [45]. This image dependence is especially noticeable in lightness direction. Sano's experiments showed that lightness differences were less noticeable than chroma and hue differences and confirmed that the background (i.e. the colour of pixels) influence is more significant on colour difference evaluation for complex (natural) images than for colour patches. Furthermore, Wichmann demonstrated that colour, contrast, saliency and image segmentation influence recognition's memory [25]. Wichmann's experiments confirmed that the colour is a highly salient visual attribute which increases subject's attention.

When dealing with the perception of colour images, visual contrast sensitivity plays an important role in the filtering of visual information processed simultaneously in the various visual "channels". The high frequency active channel (also known as parvo-cellular or P channel) enable detail perception; the medium frequency active channel allow shape recognition, whereas the low-frequency active channel (also known as magno-cellular or M channel) are more sensitive to motion.

Spatial contrast sensitivity functions (CSF) are generally used to quantify these responses and are divided into two types: achromatic and chromatic. Achromatic contrast sensitivity is generally higher than chromatic. For achromatic sensitivity, the maximum sensitivity to luminance for spatial frequencies is approximately 5 cycles/degree. The maximum chrominance sensitivity is only about one tenth of the maximum luminance sensitivity. The chrominance sensitivities fall off above 1 cycle/degree, particularly for the blue-yellow opponent channel, thus requiring a much lower spatial bandwidth than luminance. To further complicate matters, the spatial and temporal CSFs are not separable and so must be investigated and reported as a function on the time-space frequency plane. For example, although foveal acuity is far better than peripheral acuity, many studies have shown that the near periphery resembles foveal vision for moving and flickering gratings. It is especially true for sensitivity to small vertical displacements, and detection of coherent movement in peripherally viewed random-dot patterns. Central fovea and peripheral vision are qualitatively similar in spatial-temporal visual performance and this phenomenon has to be taken into account for colour appearance modelling. Other perceptual phenomena due to spatial and temporal effects have been reported by numerous papers [28, 46–49].

Several studies have shown that the Human Visual System is more sensitive to:

- low frequencies than to high frequencies
- noise in dark and bright regions than in other regions
- distortions in regions of high activity (e.g. salient regions)
- distortions near edges (objects contours) than in highly textured areas [50].

All these spatial effects are unfortunately not taken into account enough by CIECAM97s or CIECAM02 colour appearance models. Even if numerous papers have been published on this topic, in particular in the proceedings of the CIE Expert Symposium on Visual Appearance organised in 2006 [21, 51–53], there is a need for further research on spatial effects.

The main limitation of colour imaging in the colour appearance models previously described is that they can only predict the appearance of a single stimulus under "reference conditions" such as a uniform background. These models can been used successfully in colour imaging as they are able to compute the influence of viewing conditions such as the surround lighting or the overall viewing luminance on the appearance of a single colour patch. The problem with these models is that the interactions between individual pixels are mostly ignored. To deal with this problem, spatial appearance models have been developed such as the iCAM [48, 54] which take into account both spatial and colour properties of the stimuli and viewing conditions. The goal in developing the iCAM was to create a single model applicable to image appearance, image rendering, and image quality specifications and evaluations. This model was built upon previous research in uniform colour spaces, the importance of image surround, algorithms for image difference and image quality measurement [28], insights into observers eye movements while performing various visual imaging tasks [55], adaptation to natural scenes [57] and an earlier model of spatial and colour vision applied to colour appearance problems and high dynamic range (HDR) imaging [57].

The iCAM model has a sound theoretical background, however, it is based on empirical equations rather than a standardised colour appearance model such as CIECAM02 and some parts are still not fully implemented. It is quite efficient in dealing with still images but it needs to be improved and extended for video appearance [54]. Moreover filters implemented are only spatial and cannot contribute to colour rendering improvement for mesopic conditions with high contrast ratios and a large viewing field. Consequently, the concept and the need for image appearance modelling are still under discussion in the Division 1 of the CIE, in particular in the TC 1-60 'Contrast Sensitivity Function (CSF) for Detection and Discrimination". Likewise, how to define and predict the appearance of a complex image is still an open question.

Visual Assessment Experiments

Viewing conditions

In this study, we considered the case for which the observer saw projected images on a screen in a darkened room. The average luminance of the screen (i.e. the surround) was less than 10 cd/m^2, consequently the human visual system operated in the mesopic range rather than in the typical photopic range [33]. Observers watched the images projected on a white screen with a distance about 270 cm (**Figure 2**).

The projector used for the study was calibrated daily before each session of psychovisual experiments and a MURATest (colour wheel video-colorimeter) was used to control the non-uniformity of the projection. The device used in this study (developed by the ELDIM company) has a CCD of resolution 1536×1024 and a 16 bit A/D converter. Furthermore, previous experiments done in our laboratory had shown that it has a homogeneous accuracy on whole CCD array. All test patches and reference patches projected on the screen were measured. All these measures were used to compare colour attributes assessed by observers to colour data displayed. All background patches were also measured to control and calibrate the video-projector. The viewing angle for each image was about 24°, which corresponds to a perifoveal vision. The size of images was 90 cm by 115 cm. The images were partitioned in hexagonal cells of constant size. For most of experiments the viewing angle for each patch (cell) was about 1.5°, which corresponds to a foveal vision (**Figure 3**).

The reference white was always set to the white patch of the image displayed on the screen for most of the tests or measurable onto the white screen (outside the background) for tests involving complex images. The luminance of the reference white point was set to 200 cd/m^2. The luminance of the dark wall surrounding the white screen was set to 1 cd/m^2. The luminance of the background of images (black patches) was approximately equal to 0.8 cd/m^2.

Image data sets

Two different sets of test images were used: one with a simple background, another one with a complex background. For the first set, two reference stimuli and a reference grey scale were presented to allow a better relative estimation. The test specifications of the viewing pattern used for the LUTCHI data set [27] (Figure 4). In order to be consistent with previous experiments done with the LUTCHI data set, we used the $L^*a^*b^*$ colour space for our visual assessment experiments.

The second set of test images almost entirely covered the background. No reference patch was presented in this case. For all experiments, assessments were realised with magnitude estimation technique. In this test set (shown in Figure 5), the first image (houses) corresponds to a colour image with few colours (the average value of a^* and of b^* is equal to 0), a small gamut and high spatial frequencies. The second image (girl's face) corresponds to a more coloured image with a large gamut and low spatial frequencies. Lastly, the third image (motorcyclists) corresponds to a colour image with a larger gamut and high spatial frequencies. The first image was chosen because the convex hull of its colour gamut approximately overlaps the colour gamut of background patches used for the first set of images with simple background. On the other hand, the colour gamut of the two others is more extended.

Background patches were computed to sample the colour gamut. For each test, all patches were hexagonal in shape. For each test stimulus, reference stimuli and background stimuli had the same size. Whatever the test, four reference patches (a red, a green, a yellow and a blue one) were used (Figure 6) and ten test patches were computed for each reference patch. The colour of these patches was derived from reference patches (Figure 7). The test patches were chosen to cover a large colour gamut and luminance range.

Visual assessment technique

Before the experiment started, observers were asked to adapt to the surround field and to look to a grey image for a period of five min. The first time observers participated in the experiment, a training session was conducted in order that observers did not introduce bias in the results. After being adapted, observers were asked to estimate the lightness, colourfulness and hue of the test patch displayed (e.g. Figure 8).

For the first set of experiments:

- The lightness attribute was estimated relatively to a reference grey scale. Ten lightness patches were presented from black (L = 0) to white (L = 100) on the bottom of the background. For each run the slider of the lightness scale was set to the lightness value of the reference patch. The same reference white patch was also presented right under the test patch.
- The colourfulness attribute was estimated relatively to a colourfulness scale. Two reference values had been used to shorten the colourfulness scale:

the value 0 (achromatic colour) and the value 100 (in our experiments colourfulness of colour patches was always under 100). These reference values were used in order to reduce variations between observers and to adjust all colourfulness visual results onto the same visual scale. For each run the slider of the colourfulness scale was set to the colourfulness value of the reference patch.
- The hue attribute was estimated relatively to two hue scales; a Red/Green scale and a Blue/Yellow scale (respectively a^* and b^* axes of the $L^*a^*b^*$ colour space). For each run the two sliders of the hue scales were set to the hue values of the reference patch.

For the second set of experiments, there is no reference patch, so the observer was asked to estimate the difference of hue, lightness and colourfulness between the test patch and the colour of the background. Neither reference stimulus nor grey scale was used for this second set. For each run the cursor was set to the lightness, hue and colourfulness values of the mean lightness, mean hue and mean colourfulness values of the background, respectively.

For the first set of test images, we have considered five sub-sets of tests (e.g. **Figure 9**):

- Sub-test 1: study of the influence of the lightness of background patches;
- Sub-test 2: study of the influence of the colourfulness of background patches;
- Sub-test 3: study of the influence of the hue of background patches;
- Sub-test 4: study of the influence of the size of background patches;
- Sub-test 5: study of the influence of the distance between the background patches and the central ones.

For the second set of test images, we have considered three sub-sets of tests:

- Sub-test 1: study of the influence of the size of background patches (e.g. **Figure 10**);
- Sub-test 2: study of the influence of the colourfulness of background patches;
- Sub-test 3: study of the influence of the spatial frequencies of background patches (see Figure 5)

Results of visual assessment experiments

Ten observers participated in these experiments. They were students or researchers in computer vision and image understanding (male and female, aged between 18 and 45). All had a normal colour vision according to Ishihara test. Half of them had had experiences in attending psychophysical experiments. In total, 800 judgements per observer were made. The whole assessment was divided into seven sessions (three experiments per session) each lasting approximately 40 min

Results reported in this study are plotted thanks to Quantile-Quantile plot strategy. Figures 11–14 are given to illustrate the most significant results of our study. The values entitled ‘measured L^*, C_{ab}^* or h_{ab}’ correspond respectively to the lightness, chroma or hue values measured by the MURATest. The values entitled ‘perceived L^*, C_{ab}^* or h_{ab}’ correspond, respectively, to the lightness, chroma or hue values assessed by users thanks to magnitude estimation.

Figure 11 shows two examples of hue assessment done by all observers. These examples show how colour appearance varies as a function of background in regards to the hue dimension. The conspicuous bend away from the diagonal results from the well established observation that stimulus variations along the hue dimension do not correspond to pure red–green and blue–yellow sensations [1]. As we can see on Figure 11, whatever the test considered, the hue is either over estimated for yellow colours (around 104°) or for green colours (around 145°), or under-estimated for blue colours (around 275°) or red colours (around 20°). Whatever the type of background considered, it appears that background strongly biases the perceived hue of the stimuli, for some tests by more than 40 degrees. Lastly, we have noted that the undulations in the curves are similar whatever the test but their amplitude is quite different. These curves demonstrate that the bias in perceived hue is quantitatively different from one type of background to another one.

Figure 12 shows two examples of the hue assessment when the hue of background patches is constraint to a given gamut of colours. According to the colour of the test patches and the colour gamut of the background, the hue is either under estimated or overestimated. The biases are either more pronounced or in the opposite direction when the hue of background patches is in the opposite direction of test patch.

In order to estimate the bias on each colour dimension due to each type of background we first analysed separately lightness, hue and chroma. Next, we analysed these colour dimensions together and adjusted our data according to a simple linear model (see Figures 13 and 14). Moreover, we have computed the correlation coefficient of each adjustment to check its reliability. In general, the image dependence was especially noticeable in hue direction (see shape coefficients of Figures 13 and 14). That is the reason why the results linked to lightness direction or chroma direction are not presented in this paper.

The hue versus lightness difference is shown in **Figure 13** and the hue versus chroma difference in **Figure 14**. Shape coefficients of the fitting curve show that spatial background produced large and selective shifts on colour appearance. In complex image (see Figure 14c) than with a simple background (see Figure 14a), meanwhile the shifts on lightness dimension are lower (see Figure 13). Moreover, the shifts in hue dimension are higher for *more coloured images* than for the *low coloured image* confirming the influence of the number of colour patches in the background and in their hue. Furthermore, whatever the colour dimension considered, the shape coefficients demonstrated that the shifts are higher with a complex image than with a simple background. As an example, we can compare shape coefficients of Figures 13a/13b, of Figures 13a/13c, of Figures 14a/14b, and of Figures 14a/14c.

Let us now focus on the second set of test images (i.e. images with a complex background). We can observe that the shape coefficients of the low coloured image (Test 15) and of the more coloured images (Tests 16 and 17) are noticeably different when looking for both hue and chroma dimensions (see Figure 14c). We have shown that these differences are less noticeable for the high frequencies images (Tests 18 to 20) and for the images with lower frequencies (Tests 15 to 17) when the 'segmentation' is coarser (i.e. for resolution 3, Test 20 and Test 17) than when the 'segmentation' is finer (e.g. for resolution 1, Test 18 and Test 15), as we can see on Figures 14d/14c. In such a case, high spatial frequencies are filtered by the 'segmentation' and adjustment coefficients that lean toward those of images compound of background patches (Figure 14a).

We have noticed that, whatever the test considered, the shape coefficients showing lightness shifts induced higher colourfulness shifts. For example, on Figure 13 we can see that lightness shifts (between perceived and measured values) are systematically lower than hue shifts (between perceived and measured values). This is confirmed by shape coefficients which all are lower than 1.

By and large, our results have confirmed that chroma shifts are less noticeable than lightness and hue shifts. Likewise, lightness shifts are less noticeable than hue shifts. These observations concur with other studies [45]. All our results show that the visual judgment is less accurate when the colour difference between the test patch and the reference patch is high (e.g. see Figure 13a: under a difference of hue of 40 the correlation between lightness difference and hue difference is correct, but above 40 the correspondence is bad). Lastly, our results show that the more complex the content of a scene is the more the observer's judgement is biased by the colour of the background. This confirms Webster's hypothesis in relation to 'colour perception in different environments may be systematically biased by distributions of colours in those environments'. In the colour contrast section, we will present a measure of colour contrast which could be used to study if bias due to viewing background result from both spatial contrast adaptation and spatial contrast induction.

Discussion

We have noticed that our results are significantly impacted by the duration of experiments. Such observation was already done in previous studies. For example, Wichmann [25] showed that, contrary to contrast, colour plays a major role on long term visual memory (e.g. for display duration longer than 500ms). We have also noted that the sequence of tests influences assessment estimations due to human memory effect. In general, such a question has not been extensively studied. To what extent the question was: is the viewer's current impression (for test $T + 1$) of the experiment dependent upon previous assessment (for test T)? We do think so. That was the reason why in this study our tests were carried out in a random order. More generally, we have noted that human memory effect biased the assessment estimation when the background of the image did not vary in the time from one test to the following one, and when the assessment estimation duration was higher than at least 5 s. We have also observed that viewers were quick and less accurate to assess high changes from one test patch to the following one (between tests T and $T + 1$) but slow and accurate to assess low changes (between test T and $T + 1$). Considering that differences in viewer's reaction times to background changes may reduce assessment's accuracy, the assessment time was therefore limited to a minimum of 5 s.

Four continuous grading scales were used in this study with ten-grade assessment values linearly spaced in order to help the viewer in his judgement (see Figure 8c). Even if it has been established that there is no direct psychophysical correspondence between a continuous scale and a rating scale, we observed a good correlation when the colour difference between the test patch and the reference patch is low or moderate. Nevertheless, when the colour difference is high, correlation is lower.

A simple linear model has been used in this study to fit data. The next task will be to define better fitting curves from non-linear functions, then to compute a fitting model which parameterizes these fitting functions in function of the type of background considered.

Several studies have demonstrated that colour influences considerably human visual attention when seeing natural images [58]. Furthermore, several studies have shown that contextual factors influence globally and locally the saliency of a region [43]. In order to explore whether the local saliency of a region influences its colour appearance we have introduced in the second part of our study a computational model of colour contrast.

of the local saliency of a region on the colour appearance of an image from this computational model (**Figure 15** and **Figure 16**) and to extend the study of viewing parameters to *image content* and to *surround*. The rationale will be to use the three viewing parameters, *background*, *surround* and *image content*, as inputs to colour appearance models. This means calculating new colour appearance attributes into measurable objective mathematical entities. As for the first part of the study presented in this paper, an image analyser will be used to capture reference target images under all the viewing conditions studied. These images will be analysed so as to accurately describe viewing parameters such as black level, luminance range or contrast.

Colour Contrast Measure

As mentioned previously, colour considerably influences human visual attention when seeing natural images, in particular contextual factors influence globally and locally the saliency of a region. In order to explore whether the local saliency of a region influences the colour appearance of regions we introduce in this second part of our study a computational model of colour contrast.

General workflow of the colour contrast measure

The general work flow of the proposed computational model of colour contrast measure is presented in **Figure 17**. This measure of colour contrast relies on a set of parameters organised in a hierarchical structure. The computation is based on spatial criteria and integrates low-level factors calculated on defined regions relatively to their local and global neighbourhoods.

As shown in **Figure 18**, a local neighbourhood N_i is isotropically defined around a given region of interest R_i. A local neighbourhood N_i consists of a set of regions (patches) R_j given by a coarse 'segmentation' of the original image I. Such a segmentation process is managed by averaging colour information on a mosaic of hexagonal patches [15]. All patches have the same size and they realise a pavement of the original image. The size of patches is determined according to the expected resolution of the working image i.e. the spatial density of patches (see Figure 10).

The main advantage of our approach is that it is not driven by the choice of a segmentation algorithm and by the setting of associated parameters. There is a single control parameter derived from the number of patches that the observer should see in his foveal visual field at a given distance of observation.

region of interest R_i is described by its dimensions and by its location in the working image. As previously stated, the dimensions of regions of interest are directly linked to the 'segmentation' process. A region of interest corresponds to one of the hexagonal patches of the mosaic used to compute the working image. The size of patches is adjusted according to the visual angle sustained by the fovea. It determines the number of patches captured by human eye when observing the working image at a given distance.

Colour contrast is obviously modulated by chromatic variations but also by changes in luminance. The original *RGB* image is projected into the $AC1C2$ colour space to be consistent with the three different pathways of the human visual system. Then luminance changes refer to the achromatic component A and chromatic variations refer to the red–green and blue–yellow antagonist components $C1$ and $C2$.

Let be:

- C_{ij} the colour values of pixel of coordinates (i,j).
- $\bar{C}(R_i)$ the mean of colour values of the region of interest R_i with **Eqn 1**
- $\bar{C}(N_i)$ the mean of colour values of the neighbourhood N_i with **Eqn 2**
- $\sigma(N_i)$ the variance of colour values of the neighbourhood N_i with **Eqn 3**
- $\sigma_C(N_i)$ the chromatic variance computed from $\sigma_{C_1}(N_i)$ and $\sigma_{C_2}(N_i)$ with **Eqn 4**
- $\bar{C}(I)$ the colour mean of the original image I with **Eqn 5**
- $\sigma(I)$ the colour variance of the original image I with **Eqn 6**
- $\sigma_C(I)$ the chromatic variance of the original image I computed from $\sigma_{C_1}(I)$ and $\sigma_{C_2}(I)$ with **Eqn 7**

Then, we can define the following local and global parameters:

1. Local luminance contrast between a region of interest R_i and its neighbourhood N_i as **Eqn 8**
2. Local colour contrast between a region of interest R_i and its neighbourhood N_i as **Eqn 9**, with $contrast_{C_1}(R_i/N_i)$ and $contrast_{C_2}(R_i/N_i)$ expressed by Eqn 8 where $C1$ and $C2$ replace A.
3. Luminance $contrast_A\left(R_i/N_i^{\pm 15^\circ}\right)$ between a region of interest R_i and a surrounding $N_i^{\pm 15}$ which sustained a visual angle of $\pm 15°$ from the centre of R_i. The term $contrast_A\left(R_i/N_i^{\pm 15^\circ}\right)$ is expressed as $contrast_A(R_i/N_i)$ and $N_i^{\pm 15}$ consists of 6 hexagonal patches at resolution 1, 36 hexagonal patches at

As previously explained, a neighbourhood N_i is associated with each region of interest R_i. Each neighbourhood is isotropic and consists of a set of 6 hexagonal patches. A local contrast depends on both the local spatial structure of the scene and the size of the area where the local contrast is quantified. Then, the measure of the colour contrast has obviously to integrate the neighbourhood N_i of a region of interest R_i but also the local surrounding of R_i. Such a surrounding is isotropic and it is defined by a more or less important number of hexagonal patches. This number of patches is related to the expected resolution of the processed image at a given distance of observation.

4. Chrominance $contrast_{C_1}\left(R_i/N_i^{\pm 15^\circ}\right)$ and $contrast_{C_2}\left(R_i/N_i^{\pm 15^\circ}\right)$ between a region of interest R_i and its surrounding $N_i^{\pm 15}$. The terms $contrast_{C_1}\left(R_i/N_i^{\pm 15^\circ}\right)$ and $contrast_{C_2}\left(R_i/N_i^{\pm 15^\circ}\right)$ are, respectively, expressed as $contrast_{C_1}\left(R_i/N_i\right)$ and $contrast_{C_2}\left(R_i/N_i\right)$ where $N_i^{\pm 15}$ replaces N_i.
5. Colour $contrast_C\left(R_i/N_i^{\pm 15^\circ}\right)$ between a region of interest R_i and its surrounding $N_i^{\pm 15}$. The term $contrast_C\left(R_i/N_i^{\pm 15^\circ}\right)$ is expressed as $contrast_A\left(R_i/N_i\right)$, where $N_i^{\pm 15}$ replaces N_i.
6. Global luminance contrast between a region of interest R_i and the overall image I as **Eqn 10**.
7. Global chrominance $contrast_{C_1}\left(R_i/I\right)$ and $contrast_{C_2}\left(R_i/I\right)$ between a region of interest R_i and the overall image I. The terms $contrast_{C_1}\left(R_i/I\right)$ and $contrast_{C_2}\left(R_i/I\right)$ are, respectively, expressed as $contrast_{C_1}\left(R_i/N_i\right)$ and $contrast_{C_2}\left(R_i/N_i\right)$ where I replaces N_i.
8. Global colour $contrast_C\left(R_i/I\right)$ between a region of interest R_i and the overall image I. The term $contrast_C\left(R_i/I\right)$ is expressed as $contrast_A\left(R_i/N_i\right)$ where I replaces N_i.
9. Weight of a region of interest R_i relatively to its eccentricity from the centre of image I as **Eqn 11**.

   where α represents the viewing angle between the region R_i under study and the central region R_o of image I.
10. Resulting contrast of a region of interest R_i in function of the luminance as **Eqn 12** with **Eqn 13**.

The more $W_{contrast}\left(R_i\right)$ tends toward zero the less the contrast in luminance is high. If $W_{contrast_A}(R_i) \leq 1$ then the local contrast between the region of interest R_i and its local neighbourhood N_i is insignificant with regard to the contrast between R_i and the surrounding $N_i^{\pm 15}$ and in regards to the global contrast between R_i and the whole image I. Conversely, the more $W_{contrast_A}(R_i) \geq 1$ the more the local contrast is noticeable.

11. Resulting contrast of a region of interest R_i in function of the chrominance $R_{contrast_C}(R_i)$. It is expressed as $R_{contrast_A}(R_i)$ with $contrast_C(R_i/N_i)$ and $W_{contrast_C}(R_i)$, respectively, replacing $contrast_A(R_i/N_i)$ and $W_{contrast_A}(R_i)$. The term $W_{contrast_C}(R_i)$ is given by **Eqn 14**.

As shown by the flow chart of Figure 17, the achromatic information is used to compute both a global contrast measured between each region of interest and the overall working image and a local contrast measured between each region of interest and its associated neighbourhood. A local contrast and a global contrast are calculated in the same way from the chromatic information.

The final measure of the colour contrast is given by **Eqn 15**.

The colour contrast measure integrates chromatic and achromatic information weighted by the location of regions of interest. Such an approach is consistent with the non uniform distribution of photoreceptors across the human retina.

Results of the colour contrast measure

Figure 19 presents intermediate results used to construct the final measure of colour contrast. The original image contains high spatial frequencies and has a global colour mean different to zero. The image has been 'segmented' at resolution 2 (Figure 19b). It means that each region of interest R_i (each hexagonal patch) sustains a visual angle of 5° at the selected distance of observation. In the 'segmented' image, the colour of 3 patches has been changed (Figure 19c). The difference from the original colour and the modified one is great for the first patch (in the brown area at the bottom of the segmented image), moderate for the second patch and low for the third patch.

Figure 19d presents the measure of the local luminance contrast normalised by regional and global luminance contrasts. This normalised local luminance has been calculated with Eqn 13 for each region of interest R_i of the image of Figure 19c. The most salient region in terms of luminance is the white patch located in a more or less brown uniform area.

Figure 19e presents the measure of local colour contrast normalised by regional and global colour contrasts. This normalised local colour contrast has been calculated with Eqn 14 for each region of interest R_i of the image shown in Figure 19c. The white patch salient in terms of luminance contrast is also identified as salient in terms of colour contrast. Even if there are a lot of different colours in the 'segmented' image, only two patches have a significant colour contrast relative to their environment.

Chromatic and achromatic information are merged according to their relative strength to provide the final measure of colour contrast. Only the regions of interest salient for both local normalised luminance contrast and local normalised colour contrast are promoted. As shown by Figure 19g, the white patch having a high local contrast in luminance and a high local contrast in colour is associated with the highest value of the final measure of colour contrast. The measure of colour contrast introduced in this paper integrates a modulation based on an eccentricity function as the one presented in Figure 19f. Such an eccentricity function simulates the non uniform acuity across the whole visual field of a human observer.

Figure 20 shows an example of the outcome of measuring colour contrast as proposed in this paper. Figures 20b and 20c show respectively the result of the measure of colour contrast without and with the eccentricity function. Then the complete result presented in Figure 20c locates the highest colour contrasts as they should be perceived by an observer having his gaze directed to the centre of the image with a distance of observation such that a set of 7 patches would be projected on his fovea.

Another example is shown in **Figure 21**. Likewise Figures 21b and 21c show the results of the measure of colour contrast without and with the eccentricity function. Then the complete result presented in Figure 21c locates the highest colour contrasts as they should be perceived by an observer having his gaze directed to the centre of the image with a distance of observation such that a set of 7 patches would be projected on his fovea.

In the examples shown in **Figure 22** and **Figure 23**, the parts (c) to (e) have been observed by five volunteers. Their fixation points have been recorded by an eye tracking system during a free viewing task. The first four fixation points are reported on images: the red circles correspond to the first fixation, the green to the second, the blue to the third and the yellow to the fourth. Eye tracking results show that the first fixation points are located in the central area of the observed image when there is no region of interest with a high colour contrast. This central area corresponds to a visual field of around 15°. Such an area has the size of the surrounding used in the proposed model. We can see that the more a patch is important. On the other hand, the more a patch is distant of the gamut of the overall image, the more it is salient.

Discussion

In this third part of the paper we have proposed a computational method to measure colour contrast. In order to explore whether the local saliency of a region influences its colour appearance the proposed approach combines local and global information and takes into account interactions between chromatic and achromatic signals. The spatial features of the scene as well as the location of variations have been integrated in the evaluation of the colour contrast. The model has been developed to be consistent with human perception. To check the correlation between results given by the measure of colour contrast and observer valuations, eye tracking experiments were conducted with five volunteers. The recorded fixation points have been compared with the location of the highest values of colour contrast. The first experimental results are very encouraging and clearly suggest that the measure of colour contrast we have introduced in this paper is correlated with human perception.

According the authors' opinion the future of visual attention models will follow the development of perceptual multiscale saliency map based on a competitive process between all bottom-up cues (orientation, intensity and colour). Likewise, the future of visual attention models will pass by the development of new saliency models which better take into account colour perception through neural mechanisms. For example, ROI detection based on visual attention mechanisms is currently an active research area in the image processing community.

General Discussion and Perspectives

The examination of numerous visual assessment results done showed that the influence of the background on colour appearance is more noticeable:

- for *complex images* than for images with a *simple background* (see Tables **1** and **2**),
- for complex images with high frequencies than for colour images with low frequencies or simple images,
- for chromatic images with a large gamut than for less coloured images with a low gamut.

The visual assessments reported in Tables 1 and 2 were carried out using the magnitude estimation technique. Other effects on colour appearance due to patch sizes, distance between patches, lightness, chroma and hue are less noticeable than the three previous factors.

From the results and trends observed in this study, simple rules could be proposed to predict the colour appearance of complex scenes which can serve as a guide for designers.

For a more precise prediction of the colour appearance of complex images we should conduct further more specific experimental campaigns, limited to a single parametric factor study such as local saliency in the image, in order to be able to model the relative influence of each parametric factor independently of any other parametric factor. In order to explore whether the local saliency of a region influences its colour appearance we introduced a new protocol of experiments (see Figures 15 and 16) and developed a computational model of colour contrast. The next step of our study will consist of validating the proposed model and the parametric factors used from experiments carried out. The objective will be to use the three viewing parameters, *background*, *surround* and *image content*, as inputs to colour appearance models. This means calculating new colour appearance attributes into measurable objective mathematical entities.

Conclusions

In this paper, we have investigated whether the colour perception is affected by the distribution and the spatial organisation of colours in a complex image. We have analysed the influence of scene content and of background types on the colour appearance judgement. It was concluded that, for a more precise prediction of the colour appearance of complex images one should conduct further experiments campaigns more targeted, limited to a single parametric factor study such as local saliency in the image, in order to be able to model the relative influence of each parametric factor independently of any other parametric factor.

The influence of the local colour saliency on the colour appearance was also analysed. The proposed model integrates in a single model the influence of average colour perception and the interactions between local and global spatial structures according to the visual eccentricity. The measure of colour contrast relies on a set of parameters organised in a hierarchical structure. The computation is based on spatial criteria and integrates low-level factors calculated on defined regions relatively to their local and global neighbourhoods.

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