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On the Role of Color in Visual Saliency

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Abstract

Visual attention refers to the cognitive mechanism that allows us to select and process only the relevant information arriving at our eyes. Therefore, eye movements will have a significant dependency on visual attention. Saliency models, trying to simulate visual gaze and consequently, visual attention, have been continuously developed over the last years. Color information has been shown to play an important role in visual attention, and it is used in saliency computations. However, psychophysical evidence explaining the relationship between color and saliency is lacking. The results of the experiment will be presented aiming at studying and quantifying saliency of colors of different hues and lightness specified in CIELab coordinates. In the experiment, 12 observers were asked to report the number of color patches presented at random locations on a masking gray background. Eye movements were recorded using an SMI remote eye tracking system and being used to validate the reported data. In the presentation, we will compare the reported data and visual gaze data for different colors and discuss implications for our understanding of color saliency and color processing.

Introduction

It was shown that our eyes receive between 10^8-10^9 bits of data every second [1]. Most of this data is irrelevant, and if our brain processed it would drastically decrease brains efficiency. Processing and storing only the most relevant information; allows us to save energy. Human visual attention plays a major role in the selection of the information.

Visual attention is affected by two different but at the same time related groups of mechanisms: top-down and bottom-up attentional controls [2]. The top-down mechanism is voluntary and drives attention to certain features, depending on the task, knowledge and expectations of the observer. On the other hand, bottom-up mechanisms rely on the characteristics of the stimuli and their salient locations. Bottom-up attention is fast, involuntary, and most likely feed-forward. The two mechanisms are considered independent [3], but they are fully coordinated with each other when it comes to define the eye gaze of a specific observer in a particular visual scene.

In the recent decades, many computational models have tried to achieve an understanding of the visual attention, mainly from the characteristics of the visual scene (bottom-up) [4]. These models calculate saliency maps, which represent the regions and points of a visual scene which are more likely to catch out the attention. To extract the salient areas from a visual scene, the information is separated and analyzed for different features. Originally, these features were the three proposed by the feature integration theory (FIT) [5]: color, intensity, and orientation. Later on, other features have been added, such as motion, skin hue, face, horizontal line, wavelet, gist, center-bias, curvature, spatial resolution, optical flow, flicker, multiple superimposed orientations (crosses or corners), entropy, ellipses, symmetry, texture contrast, depth, or local center-surround contrast.

Computational saliency models are of a high importance and have a broad range of applications in computer vision and robotics such as image quality assessment, segmentation, compression, scene classification, object recognition and detection and many others. Therefore, it is crucial to have a robust and accurate saliency computational model, agreeing with the human visual behavior.

It has been shown that color plays an important role in the visual saliency [6], but there is a lack of psychophysical evidence showing how color characteristics differently affect our attention. This work aims to overcome the lack of evidence with an experiment designed to understand how different color characteristics affect our way to analyze and observe a scene. In this experiment, we use a signal detection paradigm and eye-tracking techniques while observers are asked to detect and report color targets.

Background

This section reviews related work and background information important for the present study. Firstly, we describe the workflow of the basic cognitive visual attention models and their computation of the color saliency. Secondly, we review several psychophysical experiments described previously, which focus on achieving a better understanding of the processes involved in color attention.

The computational saliency models try to predict the points and areas of a visual scene that will likely attract visual attention. The first saliency model, proposed by Koch and Ullman [7], was based on the FIT; it described the input scene according to three different features: color, intensity, and orientation. Lately, a complete implementation and verification of this model was proposed by Itti et al. [8].

The model extracts and analyzes independently the information for each feature, computes their relative saliency to create corresponding conspicuity maps, and combines them together into a final saliency map. The extraction of the color saliency is inspired by the processing in the early human visual system, where light of different wavelength is detected by the different retinas cones and is processed using a center-surround shape of the neuronal receptive fields in opponent color channels.

Ittis model takes an *rgb* image and extracts four different channels for color information: red (R), green (G), blue (B), and yellow (Y). These four colors correspond to the different combination of cones in the ganglion and bipolar cells, then these cells form a neural on-center off-surround field contrasting the opponent colors. Hence, to simulate this process the model creates a central field with different sizes $c \in \{2,3,4\}$ and a surround field $s = c + \delta$ where $\delta \in \{3,4\}$. Then it computes the center-surround contrast between the opponent colors.

$$\begin{aligned}\mathscr{RG}(c,s) &= |(R(c)-G(c)) \ominus (G(s)-R(s))| \\ \mathscr{BY}(c,s) &= |(B(c)-Y(c)) \ominus (Y(s)-B(s))|\end{aligned} \tag{1}$$

Contrast of the different center and surround sizes are normalized by the function $\mathscr{N}(.)$, promoting unique and strong peaks of saliency. Afterwards all the color contrast maps are combined into the conspicuity map.

$$\overline{\mathscr{C}} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} \left[\mathscr{N}(\mathscr{RG}(c,s)) + \mathscr{N}(\mathscr{BY}(c,s))\right] \tag{2}$$

Finally the saliency map of the scene will be the result of averaging the conspicuity maps of the three features: color ($\overline{\mathscr{C}}$), intensity ($\overline{\mathscr{I}}$), and orientation ($\overline{\mathscr{O}}$).

$$S = \frac{1}{3}\left(\mathscr{N}(\overline{\mathscr{C}}) + \mathscr{N}(\overline{\mathscr{I}}) + \mathscr{N}(\overline{\mathscr{O}})\right) \tag{3}$$

Ittis et al. [8] computation of color saliency is replicated in the vast majority of cognitive saliency models proposed by others.

The computation of the salient information of the color feature assumes and uses equal weighting when computing the contrast between the opponent colors (1), when combining the different center-surround contrasts (2), and when combining the three features into the final saliency map (3). Neither of these equalities is supported by a psychophysical experimental evidence.

Moreover, data from several studies contradict the color computation process utilized by Itti et al [8]. Thus, color features were found to have a higher contribution to the visual attention than intensity features [9]. It was demonstrated in an experiment where two stimuli were shown to participants simultaneously on the same shared background. The background was formed by a random distribution of pixel colors controlled in the CIELAB color space. The central portion of the two stimuli was defined by different color distributions, having a predominant deviation along either of the three axes in the color space. The participant was reporting each time which of the two centers over the common background was more apparent or salient. After testing all the possible combinations for both backgrounds and centers, it was shown that the centers with large deviations along the chromatic axes (a^* and b^*) were reported as significantly more salient than the centers with the similar deviation on the lightness axis (L^*). The second experiment validated the findings; a modification of the color saliency computational method was proposed giving more importance to the changes in color than the changes in intensity. The accuracy of the proposed method and the Ittis method was calculated and compared using eye tracking data as a ground truth to show the 17.05% increase in accuracy.

Wool et al. [10] compared the saliency of unique and non unique hues in a visual search task. They found that yellow targets had an advantage in terms of detection when compared to the blue targets. In their experiment a set of stimuli was created as random binary distributions containing both, unique and non-unique colors with the varying number of patches of one of the colors. Participants task was to count and report the number of patches they could detect. The saliency of different patches was measured by the reaction time (RT) and the number of saccades. Results did not find any advantage in the search task for unique hues, but it did find an overall advantage for yellow patches; RT was significantly shorter and the number of saccades lower when counting yellow patches compared to the blue ones.

Mean and Standard Deviation of the Stimuli Possible Background Distributions

	B_1	B_2	B_3	B_4
$\bar{L^*}$	50	50	25	75
$\sigma(L^*)$	25	1	1	1

Methodology

In the previous section, there were presented discrepancies between the computation of color saliency and psychophysical findings. In our work, an experiment is presented which aims to study the contribution of specific colors to the visual attention. In the following section, all the details of the experiment are presented.

Design of stimuli

The stimuli is composed of random distribution patterns, to avoid showing any familiar shape or object, so only bottom-up mechanisms are employed during the experiment. Both mean and standard deviation of these patterns are controlled under CIELAB color space. The random distribution is formed at a pixel level. The stimuli are set to be a square of 1440 $\times$ 1440 pixels, corresponding to $28.98^o \times 28.98^o$ visual angle degrees for the participant's view. The range of colors used to form the distributions is limited to have the same availability of chromas C^* for each specific hue angle h^o and lightness L^*.

The background of the stimuli is set to have a random distribution pattern with always mean in the center of the chromatic axes ($a^* = 0$ and $b^* = 0$), and lightness mean variates depending on the case. The observer faces four different kinds of background lightness distributions; in the first instance (B_1) the distribution covers all the possible L^* values, meanwhile the other three background cases (B_2, B_3, B_4) are be limited to lightness values $L^* \in \{25, 50, 75\}$, respectively. Therefore, each of the background will have an specific lightness mean $\bar{L^*}$ and standard deviation $\sigma(L^*)$ (see table 1). The reason for selecting these background is to be able to study if there is a difference when average lightness changes (B_2 - B_3 - B_4) or when the average is fixed but the standard deviation changes (B_1 - B_2).

The stimuli contain a fixed number of patches, which are also random distribution patterns. The lightness distribution of the patch will be at the same mean and σ as the background, and the means C^* and h^o will be specified for each case; this selection of values is made trying to cover the entire CIELAB color space (4).

$$\begin{aligned}\bar{L^*_P} &= \bar{L^*_B} \\ \bar{C^*_P} &\in \{1.3, 1.675, 2.05, 2.425, \ldots, 9.925\}_{1\times24} \\ \bar{h^o_P} &\in \{10^o, 30^o, 50^o, 70^o, \ldots, 350^o\}_{1\times18}\end{aligned} \tag{4}$$

In that way, a given patch P will be a random distribution pattern

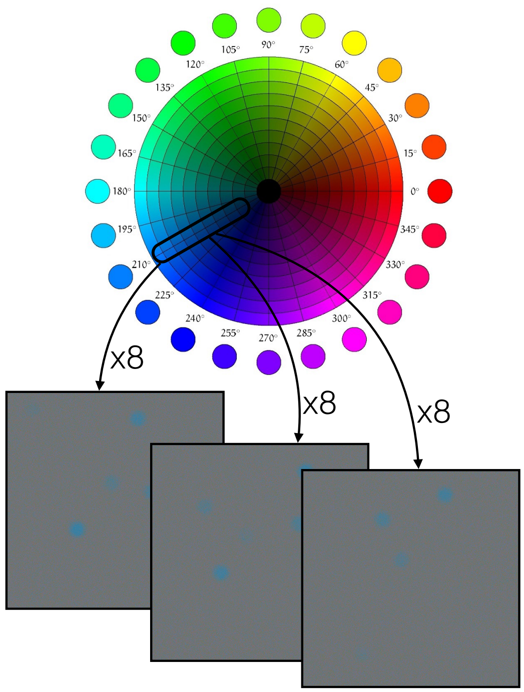

Figure 1. Diagram example of the creation of patches process for the 24 chromas of the specific hue $h^o = 210^o$ and the background case B_2.

with the same lightness mean as the background, one of the 24 possible values $\bar{C}_P^*$ as a mean chroma and one of the 18 possible hue angles $\bar{h}_P^o$ as a mean hue. The patchs spatial shape is a circle with smoothed edges. Therefore, there is no abrupt change between the patch and background, avoiding the patch being detected by the shape or edge detection mechanisms, and presumably only allowing a color detection. The patch was made to have a diameter of 98 pixels on the screen, which corresponded to 2^o of the visual angle for the observer.

Each stimulus contains eight patches of the same hue value but a different chroma. The 24 possible chromas for a specific hue and lightness are distributed into three stimuli (see figure 1). Patches are placed in random locations within the stimuli with a constraint that two patches cannot be closer than 2^o one from another.

Consequently, all the specified chroma values for a particular hue and lightness are contained in the three stimuli. This process was randomized for each hue, each lightness, and each observer; as a result, there was never a repeated stimulus pattern shown. This randomization allowed to reduce many of the biases that could be produced by the patches locations.

Participants

A total number of 12 observers participated in the experiment (seven female and five male observers). They had an average age of 24.14 years with the standard deviation of 1.23 years. All the participants were students at Rochester Institute of Technology. They all had normal or corrected-to-normal visual acuity. Due to the character of the experiment, participants' color vision was tested before the experiment by completing the Farnsworth-Munsell 100 Hue color vision test, only allowing to participate observers with the normal color vision. None of the subjects knew the precise goal of the experiment. They were only told that we are interested in understanding how people perceive different colors. The Institutional Review Board at Rochester Institute of Technology approved the recruitment of participants and the experimental procedure.

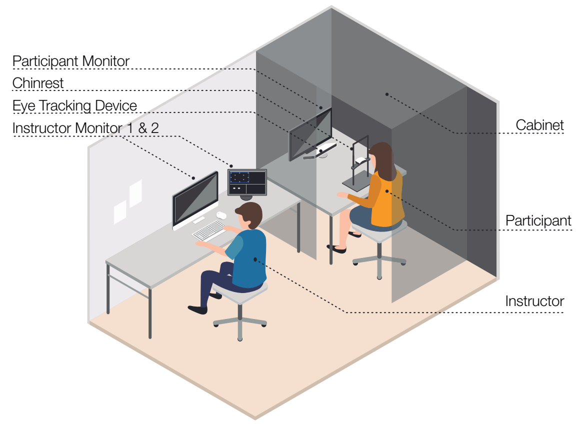

Figure 2. Illustration showing the set up in the room where the experiment was conducted.

Apparatus

Stimuli were presented using a calibrated LCD monitor ColorEdge CG277 manufactured by EIZO, Inc., using their backlight illumination of a wide-gamut LED. The monitor operated at 2560 $\times$ 1440 pixels, with the screen' physical size of 59.7 $\times$ 33.6 cm and a pixel size of 0.233 $\times$ 0.233 mm. The display was placed at the 65 cm distance from the participant.

The monitor was calibrated using an external spectroradiometer i1 Pro 2 profiler manufactured by X-Rite, Inc. The spectroradiometer had a spectral range of 380 - 730 nm reporting in 10 nm steps. It uses a geometry $45^o/0^o$ with an aperture of 4.5 mm. The monitor was calibrated to a D_{65} white point. The three primaries measured had xy coordinates $[0.6876, 0.3063]$ for red, $[0.2069, 0.7059]$ for green, and $[0.1483, 0.069]$ for blue; producing a gamut wider than both sRGB and AdobeRGB standard profiles. The monitor was set to have a luminance of 80 cd/m^2 and a gamma of 2.2 for each of the three primaries.

The experiment was conducted under a controlled lighting environment, with a temperature of 6500 K and a lightness level of 55.81 lux. The participant sat in a cabinet with neutral gray walls, where no chromatic reflection has occurred.

Eye movements of the participants were recorded using the eye tracking device RED250 manufactured by SMI, Inc. The eye tracker technology is an image based pupil with corneal reflection. It had a temporal resolution of 250 Hz, calibrated with a 9 points matrix, a spatial resolution of 0.03^o and a gaze accuracy of 0.4^o. The eye tracker was placed below the monitor at the distance of 65 cm from the observer's eyes.

An illustration of the experimental set up can be seen in Figure 2.

Procedure

Before the experiment, participants adapted to the controlled environment lighting (6500 K) during 15 minutes. Afterward, they conducted the Farnsworth-Munsell 100 Hue color vision test; it was a computer-based test done on the same calibrated display in which the experiment was run. The subject sat in the cabinet and placed his/her chin in a chin-rest, 65 cm from the monitor. During the experiment, the instructor was situated outside the enclosure controlling the experiment via the second computer. The participant was introduced with the task and was shown three example stimuli. After the observer confirmed the understanding of the procedure, the test started.

The task of the observer was to report the number of patches perceived for each stimulus. The reporting was done by saying the number out loud. The instructor was recording the number and operating the presentation program to display the next stimulus. There was no time limit, and the stimuli were shown in random order with respect to hues and lightness backgrounds. In between the stimuli, three seconds of a dark screen with the central cross was shown; pause was done to reduce a possible adaptation issue and to avoid the appearance of afterimages.

A total number of 216 stimuli were shown to each observer. After stimuli number 72 and 144 the observer was offered a break which lasted around 5-10 minutes. Before each part of the experiment started, and every time the observer moved his head out of the chinrest, an eye tracking calibration was done. The calibration was a 9 point matrix of crosses where the subject had to fixate the gaze. The experiment was controlled from a second monitor running MATLAB (MathWorks, Natick, MA) with the Psychophysics Toolbox [11] and was connected to the calibrated display. The eye tracking device was also connected to the instructor's computer, so it could be controlled by the same script in MATLAB.

The total time required to conduct the experiment, including adaptation, color vision test and running the experiment was approximately 80 minutes.

Results

The relative salience of a specific patch depends on the difference between the patch itself and the background. In our case, each patch has a distribution differing from the rest in either lightness, hue or chroma. The design of the stimuli and the task performed allows investigating saliency of each color characteristic.

Data recorded from both the participant's report (number of patches reported and time taken to report) and the participant's eye movements is analyzed depending on the hue angle and lightness values of the patches.

Hue angle

Patches of 18 different hues were displayed to the observer. For each hue, the participant saw the same number of patches and with the same set of lightness and chroma values. Therefore the probability of a specific hue patch being reported or fixated is a referent of saliency, the more a hue catches our visual attention, the higher the chance of the patches of this hue being reported. The results of computing the different probabilities (see figure 3) were calculated by using all the patches from various chroma and lightness values, but sharing the same hue angle.

The probability of reporting changes significantly for different hues; ANOVA test shows $p < 10^{-12}$. Both red and blue hues have the highest probability; meanwhile, the lowest probability is in yellow hues. Comparing the specific hues used in the process of color opponency shows no significant difference between red and green hues ($p = 0.12$) but significant difference is found when comparing yellow and blue patches ($p < 0.0014$). The probability of fixating differs from the patterns previously seen. In this case, red hues are less fixated than the rest; meanwhile, the opponent green hues, are the most fixated. The difference between the two hues is significant ($p < 10^{-4}$). No significance appears between yellow and blue hues ($p = 0.869$). The overall difference of probability of fixation for different hues is also significant ($p < 10^{-4}$). In the previous results, it could be seen a clear differentiation between reporting and fixation probabilities. Greens appear to be more fixated than reds, but this does not seem to affect the reporting process. In contrast, blues are more reported than yellow, while their probability of fixation is not significantly different. Notably the pronounced differences are found for the opponent hues (red, green, yellow and blue). At the same time the rest of hues (orange and cyan) appear to be within the average value range, except for the magenta hue which has a high number of fixations yet is less reported than rest.

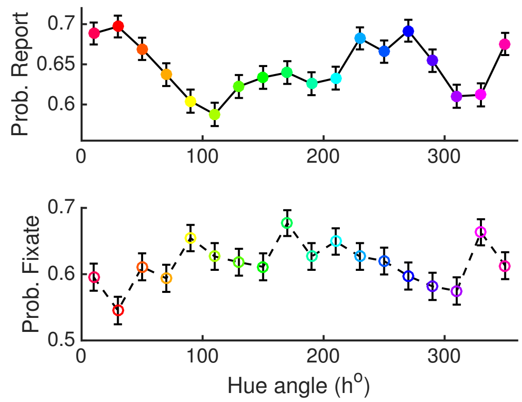

Figure 3. *Probability of a patch being reported (top) and being fixated (bottom) by each patch hue angle. Error bars denote the standard error of mean (SEM).*

Chroma is the variable that influenced the detection of the patch. The lowest chroma value was not reported for any of the stimuli. At the same time, the highest chroma value was always reported. Therefore, the probabilities of reporting and fixating for different hues depending on chroma values were analyzed separately (see figure 4). The probabilities of reporting have a cumulative Gaussian shape; the 0.5 percentile is at chroma values 4.28 for red, 4.67 for green, 4.16 for blue, and 4.78 for yellow. It can be observed that the probabilities of fixation never reach 0 or 1. Since observers were performing a search task, they could potentially randomly fixate an area where a non-perceived patch was located. Therefore, the probability of a patch being fixated by a random fixation was calculated ($P_{rand} = 0.29$) and represented as the gray area in the plot (figure 4). It can be seen that the patches with the low reporting probability have a considerably higher fixation probability. The fact of no patches with probability of fixation equal to 1 might be due a non-necessity of a precise fixation

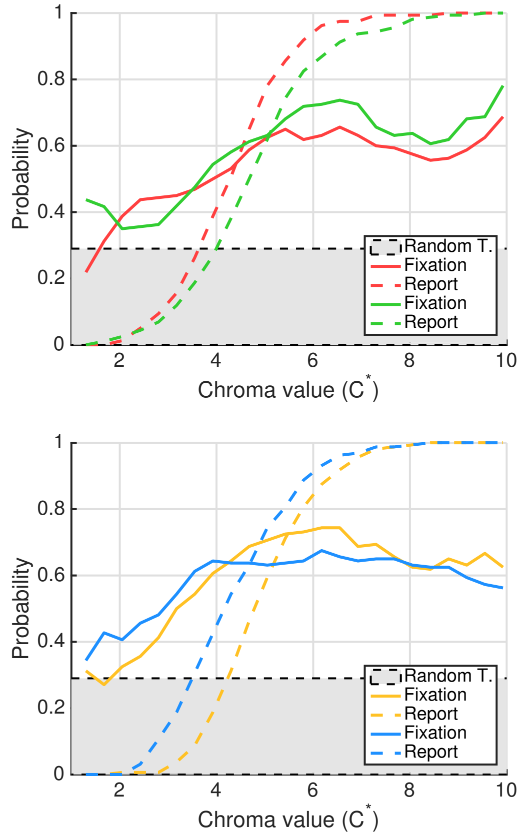

Figure 4. *Probability of report (dashed line) and probability of fixation (solid line) by different chroma values. The plots are comparing green vs red (top) and blue vs yellow (down). The gray area represents the probability of a patch being detected by a random fixation.*

centered on the patch in order to detect and report it. This effect is more predominant for high chroma values, where the probability of fixation is lower than for the mid-range chroma values.

There is an increase in reporting red patches compared to the green patches, although it was shown not to be significant. Green patches were significantly more fixated overall than red ones, but this effect is only observed for high chroma patches; while for the low chroma patches, there is no significant difference.

Regarding blue versus yellow hues, a significant advantage in reporting blue patches was found. Although the overall probability of fixations for blues compared to yellow hues did not show any significant difference, the viewing behavior changes noticeably for low and high chroma values. The advantage of blue against yellow remains in the fixation probability of low chroma values; nevertheless in high chroma values yellow appear to have a higher probability of fixation.

Lightness value

The stimuli presented to the observer had four different cases of lightness distributions: three of them with the same lightness standard deviation but variating in mean (B_2, B_3, and B_4) and two with a common mean but changing in standard deviation (B_1 and B_2). In a given stimulus both background and patches shared the same lightness distribution.

Results for each Lightness Distribution Case

	B_1	B_2	B_3	B_4
Prob. Report	**0.589**	**0.686**	**0.662**	**0.647**
	0.0068	*0.0064*	*0.0066*	*0.0066*
Prob. Fixate	**0.623**	**0.616**	**0.612**	**0.611**
	0.0095	*0.0096*	*0.0096*	*0.0096*
T. Report (s)	**31.82**	**26.36**	**27.41**	**28.78**
	1.105	*0.936*	*0.96*	*0.922*
T. Fixate (ms)	**335.6**	**332.9**	**319.5**	**347.7**
	8.281	*8.117*	*8.995*	*7.936*
# of Fix.	**13.7**	**12.79**	**12.15**	**12.82**
	0.435	*0.453*	*0.543*	*0.457*

Bold numbers represent the mean and italic numbers the standard error of mean (SEM).

The probabilities of reporting and fixating, the time taken to report the stimuli, the dwell time of fixations and the total number of fixations for each stimulus were calculated for each lightness distribution (see table 2).

B_1 compared to B_2 has a significantly lower probability of reporting ($p < 10^{-9}$) and significantly longer time needed to complete the task ($p < 10^{-4}$). The probability of fixation, the total number of fixation per stimuli, and the dwell time of fixation do not show significant differences. When comparing the different lightness means (B_2 - B_3 - B_4), a significantly higher probability of report is found for B_2 against B_3 ($p < 0.0442$) and B_4 (10^{-4}). The rest of analysis do not show significant differences, although it can be seen that less time is needed to complete the task when B_2.

Conclusions

The goal of the experiment was to study the detection and the viewing behavior in the process of visual attention to specific colors, which so far were not taken into account when computing color saliency (1) – (3).

The results showed a clear discrepancy between the reported stimuli and the eye tracking data. The highly fixated patches are not necessarily reported, and vice versa. These results suggest the presence of two different mechanisms. First one is an unconscious detection of the patch, where the physical stimuli catches the attention of the eye, but the observer is not aware of it. The second one is the awareness of the detection, when the observer consciously identifies and reports the patch. The existence of these types of mechanisms has been previously proposed [12, 13]. Our data can be considered as an experimental confirmation with respect to color detection.

The patches for all the hues used in the experiment showed that the fixations occurred for the lower chroma than the chroma for reporting. Significant differences are found for blue and yellow hues: blues are more fixated without being reported, but the tendency changes for the conscious detection with reporting, where yellow is easily fixated (a similar behavior is present for red vs. green hues). High chroma values is where the highest discrepancies between reporting and fixating are found: the highly reported hues have a lower fixation rate. As previously suggested, this can be due to the no need of a precise fixation to report highly salient patches.

Therefore advantages of some hues over others are found for both unconscious detection and aware reporting. None of these facts are taken into account when computing color saliency in existing models, where all hues contribute to color saliency in an equal weight.

The lightness level of the color it has also shown to affect the color saliency: where same color distances in different lightness level differ in their contribution to visual attention. Colors with a lightness mean $L^* = 50$ and no deviation were more easily reported than when either mean or deviation changed; these advantages are not present when looking into the fixation data.

As a future work, we propose to create a computational model that distinguish between the two mechanisms: detection and awareness. The model should apply different weighting to each hue corresponding to the results found. Furthermore, this model should adapt to both scenarios: unconscious attention (eye tracking data) and aware detection (observer report).

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