Evaluation of color spaces for user-supervised color classification in robotic vision

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Abstract—*Autonomous robots are becoming an integrated part of our daily life. The use of a robot for substituting man power in different activities that might be too dangerous, repetitive or time consuming, has become a common procedure nowadays. Robotic soccer is a research branch that focuses on developing autonomous mobile robots, using the game of soccer as a testing platform. The soccer environment in RoboCup competitions is still more controlled than the one of the regular soccer games among human teams. For the vision system of the robotic soccer players, the colors of the objects of interest are still important clues for their detection. Thus, most of the research teams attending the robotic soccer competitions, use manual or user-supervised color classification procedures before each game, in order to guarantee an accurate object detection during the game. This paper intends to be an evaluation of the most common color spaces used in image processing applications that are based on color segmentation. The paper presents a graphical application used for testing both the performance of human users in the classification of different colors, under different color spaces, as well as the performance of user supervised algorithms for color classification. The results acquired prove that the color spaces which separate the luminance information from the chromatic one, mainly the YUV color space, provide a more accurate outcome.*

Keywords: Robotic vision, color classification, user-supervised algorithms, color image segmentation.

1. Introduction

The human brain can process all the visual information provided by the eyes in a short amount of time since it possesses 10^{10} neurons, out of which, some have over 10000 synapses with other neurons [1]. Looking at each neuron as a microprocessor and considering that these microprocessors are able to work in parallel, the human CPU cannot even be compared to any computer that has been invented so far. Thus, providing a visual sense similar to the human one, to a robot, is yet a far to be accomplished task. Because of this, most of the robotic platforms that are being developed nowadays and that need to process visual information about the surrounding world, perform in environments that are controlled up to a certain extent, depending on the practical application of the robot.

The RoboCup Federation [2] is an international initiative that focuses on the development of autonomous mobile robots and provides an environment for testing the developed robots, by means of different research competitions. The research lines involved in these types of competitions focus mostly on artificial intelligence, multi-agent systems and computer vision. The initiative is formed by several leagues, one of the most popular being the Soccer League. In this league, robots have to play soccer autonomously, without any human intervention. The league is then divided in subleagues, each of them involving different types of robots. The Middle Size League is formed by teams that build their one wheeled robots, of some standard dimensions. The Standard Platform League is attended by teams using a humanoid standard platform, that is, all teams use the same robots and their contributions focus on software developments. Finally, the Humanoid League fosters teams that build their own humanoid robots. The objective of the Soccer League is having by 2050 a team of fully autonomous humanoid robots, capable to play soccer against the most recent winner human team of the World Cup.

The goal of the league is still far from being achieved, since robots still play soccer in indoor environments, that are yet controlled, up to a certain extent. The controlling factor lays mostly on the fact that in most subleagues, all the objects of interest have distinctive, predefined colors. This is, the ball is orange in most of the subleagues, except for the Middle Size League, where the ball can have any saturated color. The soccer field is green, the goal posts can be yellow, blue or black and the lines of the field are white. In this type of scenarios, as well as in many industrial applications, the processing pipe of the visual information captured by a robot has as a first step, a color segmentation procedure. Especially in controlled environments, color can be an important clue for the detection of an object of interest. The color segmentation procedures imply the definition of color ranges for all the colors of interest of the application. Defining color ranges can be done by a human user, as an offline procedure, prior to the performance of the robot [3], [4] or it can be done online, by using semi-automatic algorithms [5], [6], [7]. The representation of the colors in digital format depends on the color space chosen and so far in literature there is not a clear, unanimous choice for a certain color space that might be the most appropriate.

In this paper we present the results of a study on the use of color spaces in robotic vision, in order to understand if there is a more appropriate one to be used in these kind of applications. We intend our paper to be a contribution for the robotic soccer community but it is not limited to this. A tool for defining color ranges, both by an user and by a semi-automatic algorithm of region growing, under different color spaces, has been developed and the acquired results are presented. The results obtained facilitate the choice of a color space when implementing a vision system for robotic soccer players and its application can be extended to any computer vision procedure that implies color segmentation or classification.

This paper is structured in five sections, the first of them being this introduction. Section 2 provides an overview on the color spaces that have been included in the testing platform. Section 3 describes the features of the graphical tool that has been developed and the algorithms that have been implemented for the supervised color classification. In Section 4 the results and their discussion are presented. Finally, Section 5 concludes the paper.

2. Color Spaces

For the purpose of this study, five different color spaces were studied [8]. A color space is a mathematical model for defining and representing a color. The conversions between these five color spaces are based on linear mathematic equations [9], [10] (Subsection 2.1). Each of the color space has emerged at some moment in the history due to the necessity of rendering images on different devices or with different infrastructures. The study that the authors are proposing, aims at finding the most appropriate color space for robotic applications.

The RGB color space [11], [12] is the foundation of much visual technology, being used mostly for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography [13]. An RGB color space is an additive color space, defined by the three chromaticities of the red, green, and blue. To form a color with RGB, three colored light beams (one red, one green, and one blue) must be superimposed (Fig. 1). Each of the three beams is called a component of that color, and each of them can have an arbitrary intensity, from fully off to fully on, in the mixture. The RGB color space is not visually uniform and not very intuitive for a user to use it, as humans do not perceive color as the superimposition of the three primary colors.

The HSV color space is a related representation of points in an RGB color space, which attempts to describe perceptual color relationships more accurately than RGB [13], [14]. HSV stands for hue, saturation, value and it describes colors as points in a cone. The HSV color space is mathematically cylindrical (Fig. 2), but it can be thought of conceptually as an inverted cone of colors (with a black point at the bottom, and fully–saturated colors around a circle at the

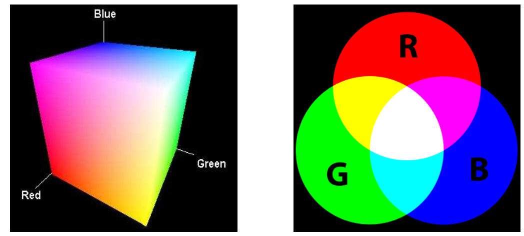

Fig. 1: On the left, the RGB cube and on the right, an example of an additive color mixing: adding red to green yields yellow, adding all three primary colors together yields white.

top). Because HSV is a simple transformation of device-dependent RGB, the color defined by the (h, s, v) triplet depends on the particular color of red, green, and blue “primaries” used.

The central axis of the cone ranges from black at the bottom to white at the top, with neutral colors between them, where angle around the axis corresponds to “hue”, distance from the axis corresponds to “saturation”, and distance along the axis corresponds to “value”. The hue represents the percentage of color blend, the saturation is the strength of the color and the value is the brilliance or brightness of the color [12]. Varying H corresponds to traversing the color circle. Decreasing S (desaturation) corresponds to increasing whiteness, and decreasing V (devaluation) corresponds to increasing blackness [12].

This color model is based on how colors are organized and conceptualized in human vision in terms of hue, lightness, and chroma, as well as on traditional color mixing methods which involve mixing brightly colored pigments with black or white to achieve lighter, darker, or less colorful colors [12]. For these reasons, the HSV color space is considered the most intuitive for human users to use it.

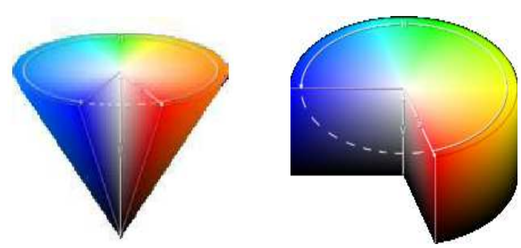

Fig. 2: The conical and cylindrical representations of the HSV color space.

The HSL color space is similar to the HSV one, the definition of hue and saturation, being the same as for the HSV color space [8]. The “value” component is replaced by “lightness” and the main difference is the fact that the value, or the brightness of a pure color is considered to be the brightness of white, whereas the lightness of a pure color is the lightness of medium gray. The geometrical representation of the HSL color space is a double cone or double hexcone [12] (Fig. 3). Although the HSL color space is used interchangeably with HSV in many texts, it was originally used to describe another (distinct) color space. Hue and Saturation are defined as for the HSV color space, but lightness quantifies the energy in a color rather than its non-blackness.

The HSI color space is yet another variation from the HSV color space [10]. The H and S components have the same meaning as for the HSV color space, while I stands for intensity and is the simple average of the three components of the RGB color space. The advantage is that this representation preserves angles and distances from the RGB cube.

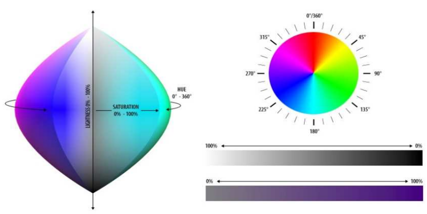

Fig. 3: The geometrical representation of the HSL color space.

In the YUV color space [10], [8], the color is represented in terms of a luminance component (Y stands for luma) and two chrominance, or color, components (U and V) (Fig. 4). This color space appeared as a necessity of introducing color television using a black and white infrastructure and encodes a color image also taking the human perception into consideration, that is, separating the luminance information from the color information.

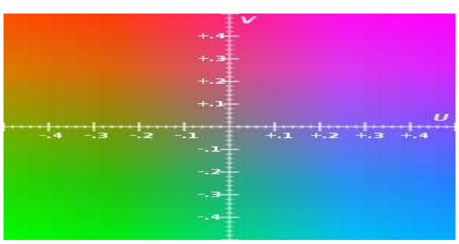

Fig. 4: Geometrical representation of U-V color plane, when Y = 0.5.

2.1 Conversions between color spaces

Conversions from one color space to another are based on mathematic expressions that are presented as follows. For the practical implementation of our application, the images used had been acquired in RGB and they have been converted to different color spaces, based on the formulas found in [10]. In all these cases, we consider the R, G and B components with values from 0 to 255.

- RGB to HSV:

$$
\begin{aligned}
V &= \max(R, G, B) \\
S &= \begin{cases} \frac{V - \min R,G,B}{V} & if\ V \neq 0 \\ 0 & otherwise \end{cases} \\
H &= \begin{cases} 60(G-B)/S & if\ V = R \\ 120 + 60(B-R)/S & if\ V = G \\ 240 + 60(R-G)/S & if\ V = B \end{cases}
\end{aligned}
$$

- RGB to HSL:

$$
\begin{aligned}
V_{max} &= \max(R, G, B) \\
V_{min} &= \min(R, G, B) \\
L &= \frac{V_{max} + V_{min}}{2} \\
S &= \begin{cases} \frac{V_{max} - V_{min}}{V_{max} + V_{min}} & if\ L < 0.5 \\ \frac{V_{max} - V_{min}}{2 - (V_{max} + V_{min})} & L \geq 0.5 \end{cases} \\
H &= \begin{cases} 60(G-B)/S & if\ V_{max} = R \\ 120 + 60(B-R)/S & if\ V_{max} = G \\ 240 + 60(R-G)/S & if\ V_{max} = B \end{cases}
\end{aligned}
$$

- RGB to HSI

$$
\begin{aligned}
V_{max} &= \max(R, G, B) \\
V_{min} &= \min(R, G, B) \\
I &= \frac{R + G + B}{3} \\
S &= \begin{cases} \frac{V_{max} - V_{min}}{V_{max} + V_{min}} & if\ L < 0.5 \\ \frac{V_{max} - V_{min}}{2 - (V_{max} + V_{min})} & L \geq 0.5 \end{cases} \\
H &= \begin{cases} 60(G-B)/S & if\ V_{max} = R \\ 120 + 60(B-R)/S & if\ V_{max} = G \\ 240 + 60(R-G)/S & if\ V_{max} = B \end{cases}
\end{aligned}
$$

- RGB to YUV
$Y = K_r R + (1 - K_r - K_b)G + K_b B$
$U = 0.5(B - Y)/(1 - K_b)$
$V = 0.5(R - Y)/(1 - K_r)$
- Constants K_b and K_r depend on the RGB color space that is used.

3. The Color Spaces Tool

In order to obtain experimental results, a graphical user interface tool has been developed. The tool has two distinctive applications. First, it can be used for the manual classification of several colors, under the five color spaces (Fig. 5). Using sliders, users can manually determine the ranges for each one of the following colors: red, blue, green, yellow, orange, white and black.

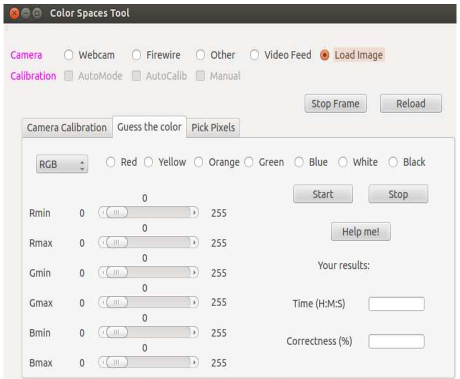

Fig. 5: Illustration of the feature of the Color Spaces Tool allowing manual classification of colors.

This feature works as follows: the user chooses an image that wants to classify, called *TrialImageX*, where X is a number identifying the chosen image. The set of trial images contains several images that have different degrees of difficulty in what concerns the color classification. That is, some of the images contain simple colored objects, without any shadows and without being affected by much noise (Fig. 6(a)). The color ranges of these objects are very close to the color ranges established in the literature, which makes the classification easier. The trial images set contains also images that might be more difficult to classify since they contain objects whose colors are affected by the illumination (Fig. 6(b)). When gathering results about this part of the study, each user has been advised to try the classification of at least one simple image and of one more complex image.

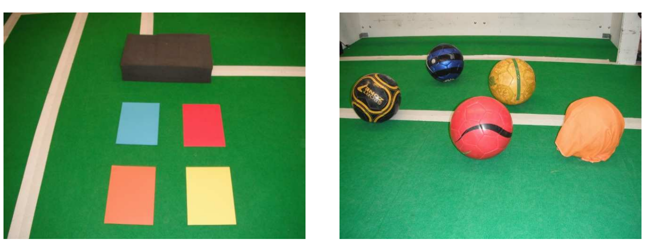

Fig. 6: On the left, an example of a simple image used for testing manual color classification. On the right, a more complex image that contains color gradients, shadows and objects with more details.

When choosing the *TrialImageX*, the *GroundTruthX* image is also loaded and will be further used for generating the results of the classification. The *ground truth* image is an image that has been already classified by an experienced user(Fig. 7). This image is considered to have the correct color ranges for all the colors and will be used for computing the correctness of the classification of each user. The correctness is calculated by direct comparison, pixel by pixel, of the images *GroundTruthX* and *TrialImageX*, when the user concludes the classification. In terms of results, the users are asked to record their correctness as well as their performance time, for each of the color spaces. The performance time is calculated by the graphical tool from the moment in which the user started the classification until the moment that he decided that his classification is correct, thus requesting it to be compared with the ground truth. At the end of all the trials, the users are asked to fill in a questionnaire that will be presented in Section 4.

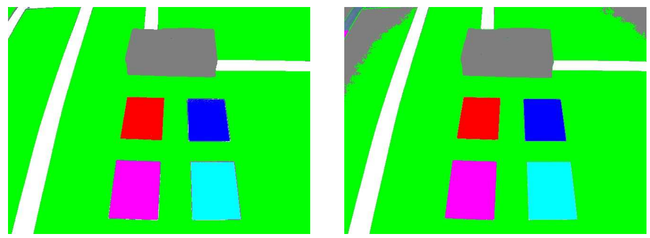

Fig. 7: On the left, one of the images used as ground truth validation. On the right, the color classification performed by an user.

For the second part of the evaluation method, we have tested two different implementations of a region growing segmentation algorithm [10], [15]. The user chooses a trial image from the same set that was already presented and the correctness of the performance of the algorithm is calculated, as before, by direct comparison to the corresponding ground truth image. This feature of the Color Spaces Tool is illustrated in Fig. 8.

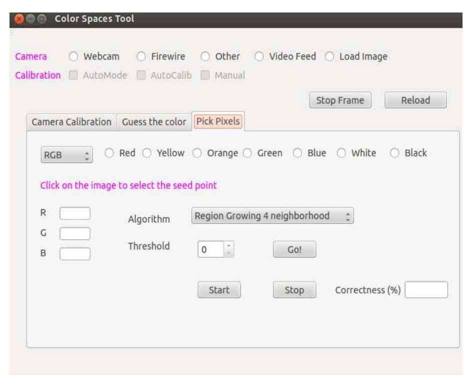

Fig. 8: Illustration of the feature of the Color Spaces Tool allowing supervised classification of the colors.

One approach was using the region growing algorithms provided by the OpenCV library [9]. The user has to choose a starting point(seed point) for each of the colors that he or she wants to classify and the algorithm will return all the pixels in the image that have the same color, +/- a predefined threshold, based on the following simple

mathematic relation:
$src(sP.x, sP.y)_r$ - infThresh $<=$ $src(x,y)_r$ $<=$ $src(sP.x, sP.y)_r$ + supThresh
$src(sP.x, sP.y)_g$ - infThresh $<=$ $src(x,y)_g$ $<=$ $src(sP.x, sP.y)_g$ + supThresh
$src(sP.x, sP.y)_b$ - infThresh $<=$ $src(x,y)_b$ $<=$ $src(sP.x, sP.y)_b$ + supThresh,

where *sP* represents the seed point, *infThresh* is the value of the threshold to be used when calculating the minimum value of the color range and *supThresh* is the value of the threshold to be used when calculating the maximum value of the color range for the classification of a pixel. In this example the algorithm is presented for (r, g, b) values of the pixels but it was used in the same manner for the triplets describing the value of a pixel in all the mentioned color spaces.

Starting from the seeding point and based on the values of the threshold introduced by the user, the algorithm will search the neighbor pixels (both 4-neighbor and 8-neighbor implementations are being tested). If the color of a neighbor pixel is in the range $[(color_{seedPoint} - infThresh), (color_{seedPoint} + supThresh)]$, the neighbor is classified as having the same color as the seed point and it is also marked as the new seed point for the following iteration. The algorithm stops when there are no more pixels to be classified.

The second approach was implementing a region growing algorithm from scratch, by the authors. The logic behind the algorithm is the same as previously described, with a small twist. Starting from the seed point, the 4-neighbors or the 8-neighbors pixel values are checked and if a neighbor's value is in the vicinity of the seed point's value (+/- a threshold), the pixel is marked as visited and is considered to be the new seed point for repeating the algorithm. The small twist for this algorithm is that the threshold value has to be the same for all of the three components that give the value of a pixel in each of the color spaces.

The presented tool can also accept video feed and configure color ranges based on direct images captured by the vision system of different robots, and can save the color ranges to a configuration file to be used in the further performance of the robot. Also, it allows manual calibration of the colormetric parameter of the camera that provides the video feed, in order to insure a proper image acquisition.

4. Results and Comments

In this section, the results obtained so far with the Color Spaces Tool will be presented and commented.

The tool has been developed for the study of color spaces when performing manual color classification, as well as for studying the same color spaces when using semi-automatic color segmentation algorithms, or what the authors call supervised color classification. For the manual classification of the color ranges, the results are presented in Table 1. A number of 15 subjects have been tested and the surprising result was that most of them had the best performance in the YUV color space, both in terms of correctness and performance time. This result is remarkable considering that in literature the idea that the HSV color space is more intuitive to humans is promoted [16].

	RBG	HSV	HSL	HSI	YUV
Average Time	5min 33s	4min 19s	4min 34s	4min 49s	4min 13s
Correctness	72%	92%	89%	85%	95%

Table 1: Table with the results obtained with the Color Spaces Tool for manual color classification.

Just like the HSV color space, in which the users actually have similar performance as in the YUV color space, the latter separates the color information into luminance and chromaticity. These characteristics make it indeed more intuitive to humans, considering it is similar to the way we perceive colors. This result is very important because most of digital cameras nowadays acquire images in the YUV color space and being able to perform the color classification in the same color space, would save important processing time that is spent in converting the YUV images to a different color space.

At the end of the trials, the subjects were also asked to fill in a questionnaire that would help the authors understand if there is any preferred or easier to use color space. The results show so far that the users preferred YUV, HSV and HSL color spaces,in this order, while RGB and HSI were more difficult to handle. All of them considered the “primary colors”, red, green and blue easier to be classified.

Table 2 presents the results in terms of correctness of the classification:

	RBG	HSV	HSL	HSI	YUV
OpenCV-4n	87%	90%	85%	72%	92%
OpenCV-8n	90%	90%	87%	77%	93%
RG-4n	80%	75%	70%	63%	85%
RG-8n	82%	78%	71%	63%	90%

Table 2: Table showing the correctness of the region growing algorithms for all the color spaces.

These results show once again that the color classification algorithm performs better in the YUV color space. Moreover, in terms of implementation logic, the results prove to be more accurate when the supervising user has the possibility of choosing different threshold values for the three components of a color, for the color classification algorithm.

As stated before, each user was asked to fill in a questionnaire concerning his interaction with the Color Spaces Tool. The questions asked are presented as follows, as well as the averaged responses of the users.

• *Are you working in the area of computer vision/image processing?*

The first question was relevant for the authors of the applications in order to establish a connection between the performance time of each user and its background in a related field. The subjects were mainly non experienced users, only 20% of them have had some experience in this field. The users that were familiar to these issues, performed slightly faster (in average, 30 seconds faster).

• *The notion of color spaces was familiar to you at the beginning of this test?*

All users replied that they were aware of the definition of a color space. However, most of them were not familiar with the characteristics of each color space. The tool has a "Help me!" button which allows the user to choose a color space and the geometrical representation of the color spaces will be displayed in a separate window, similar to the ones presented in Section 2

• *Do you think that some of the color spaces were more intuitive to use, than the others? If yes, which ones were easier to use?*

65% of the users' first choice was YUV, followed by HSL. In opposition to this, RGB was the more difficult one for all the users.

• *Do you think that some of the colors that you had to classify were more intuitive to classify than others? If yes, which ones?*

85% of the users answered that white, black and the RGB primary colors were easier to classify that the rest.

5. Conclusions and Future Work

The major issue that this study addresses is the influence of a color space in the process of color classification. For this purpose, the amount of time spent by a human user for classifying colors under different color spaces, as well as number of pixels correctly classified both manually or automatically, under the same color spaces have been recorded and the results obtained have been presented. The results that we have presented show that, contrary to common belief, human users perform better when working in the YUV color space.

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