Robust vision system to illumination changes in a color-dependent task

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Alberto Romay
Technische Universität Darmstadt

Ernst Kussul
Universidad Nacional Autónoma de México

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Robust vision system to illumination changes in a color-dependent task

Andrés Espínola[1], Alberto Romay[2], Tatiana Baidyk[3] and Ernst Kussul[4]

***Abstract*— Most computer vision tasks are strongly sensitive to illumination changes. This is the case of RoboCup competitions, being color dependent tasks, they require a robust color-based segmentation method of the image for object recognition. It is difficult to achieve a constant illumination in a work environment that is subject to day light changes. This is why camera parameters calibration such as exposure time must be robust enough to reduce the impact in the output images. A result comparison on the segmentation of images is made in three different color spaces, RGB, HSV, and YCrCb. We researched their connection with changes in lighting condition and select one of them that have less error for those environments. We introduce a fuzzy calibration method of the camera exposure time parameter, by histograms correlation. The calibrations results give an approximate value of the correct parameter to be modified in the camera in order to avoid affecting the thresholds of segmentation in the color recognition task.**

I. INTRODUCTION

RoboCup is an international scientific initiative with the goal to advance the state of the art of intelligent robots. When established in 1997, the original mission was to field a team of robots capable of winning against the human soccer World Cup champions by 2050 [1]. The robot soccer game is a standard problem where a wide range of technologies can be integrated, examined and registered. This paper examines the problem of the illumination changes than can't be controlled in the environment of the competition. While the rules of the contest provide some boundaries on the lighting conditions, in practice the lighting levels can vary between 400 - 1500 lux average illumination for different competitions depending on the soccer fields distribution inside the competition hall. In addition there may be variations of up to 500 lux for different parts of the hall. External factors may also causes variations to the mean illumination of up to 400 lux during the day at a given competition [2]. Another example is the task of mobile robot navigation in environments where the illumination is affected by the variation of light outdoor at different times of the day [3]. To solve the problem we selected two different approaches: passive and active calibration. The passive calibration is made through image segmentation with different thresholds. For this task we selected three presentations of color spaces [4]: RGB, the most common in the image processing field, the HSV space, which is a nonlinear transformation of the former and the YCrCb, the native color space of most web cams. All experiments were carried out for those color spaces to determine which is the best to use for illumination changes in the environment described. The second approach is an active calibration of camera parameters, specifically the exposure time. The auto exposure method of the cameras with which we have been working do not solves the problem correctly. The amount of light that the camera captures varies greatly from one moment to another with the movement of the camera, so the segmentation thresholds do not work with these major changes of light. We present a calibration method for the exposure time parameter of the camera by comparing histograms of the images and segmentation differences, finding the difference between them by their correlation [5] and pixel percentage match , which we use as a measure of error between the amounts of light from one image to another. We propose a fuzzy algorithm to find the exposure time in the camera needed to adjust the histograms of the images and thus does not affect the thresholds for color segmentation.

1. Master's Student. IIMAS, National Autonomous University of Mexico, Insurgentes Sur s/n, Mexico D.F. a.espinola@uxmcc2.iimas.unam.mx
2. Master's Student. Mobile Robotics & Automated Systems Laboratory, Universidad La Salle, Benjamin Franklin 47, México D.F. aromay@lci.ulsa.mx
3. CCADET, National Autonomous University of Mexico, Insurgentes Sur s/n, Mexico D.F. t.baydyk@ccadet.unam.mx
4. CCADET, National Autonomous University of Mexico, Insurgentes Sur s/n, Mexico D.F. ernst.kussul@ccadet.unam.mx

II. TASK DESCRIPTION

The vision system has been developed for a humanoid robot that participates at the RoboCup Competition in the “Humanoid Kid Size league" [6] and consists of a soccer game between autonomous robots. The goals in the soccer field are painted in yellow and blue colors as well as two color coded landmark poles are located outside the field along the mid-field line. The challenge consists in identifying the ball, the goals and the poles, where the principal source of information is the vision system. This system has to provide useful information for the robot to navigate smoothly within the workspace. One rule clarifies that the robot must be able to function without special lighting sources in the field, thus forcing the robot to rely entirely on the general lighting of the competition hall. Another problem is that these places (convention centers, expos, gyms, etc.) usually have windows that provides extra lighting that changes throughout the day from very bright to be totally absent at night, making a calibration of colors in the morning very different from one made at night. This problem is currently solved by participants making a color calibration for each time of competition, having to make four or five different calibrations for a day this being very inefficient.

A. Computational limitations

This work is originally meant to be for a very limited computational capability, in our case, a single embedded

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computer in the humanoid robot of only 45 cm height, need to make the the walking gate computation, the artificial intelligence for the decision making, path planning and the vision system, so it is really hard to implement everything to run smoothly inside the robot. In this case, the work that we will present can be extended to another kind of embedded system or low capability computer for computer vision tasks.

B. Previous Approaches

Image pre-processing transformations have been developed in several previous researches [7]. All these approaches consider a post-acquisition step. It will be better to have an improved image from the acquisition itself before starting the main vision task. We will explain some of the methods used so far for pre-processing after the acquisition.

1) Color constancy: this technique approach takes a similar idea of what is proposed in this paper. However, in order to differentiate our proposal we describe what this color constancy approaches are about.

Color constancy refers to the ability of color correction in order to get the same color information form images with different kinds of illumination. This chromaticity correction can be achieved by image values transformation based on an illuminant estimate [7]. Several methods have been use to estimate the illumination in an input image in order to transform the colors into ones previously know by an illumination reference.

Some types of these methods are called *Static Methods* which are statistics-based. Low-Level statistics-based methods assume that the color of the light source can be estimated by computing the average color in the image [8]. Tan et. al show in [9] a statistic physics-based method which use the objects in a scene in order to use information about their interaction, for example highlight regions, so they can estimate the illumination source.

Forsyth shows in [10] a gamut-based type of illumination estimation algorithm. These gamut-based methods are based in the assumption that there is only a limited number of colors that can be observed in a real-world image for a given illumination type. The principal idea of these methods is to estimate the illumination type of an unknown input scene given a precomputed gamut.

Other approaches in illumination estimation methods are learning-based. As considered in [7] gamut-based methods are separated from learning-based methods. Approaches of this kind have implemented neural networks, support vector regression and thin-plate spline interpolation to deliver an accurate color constancy based on trained data. By combining the output of multiple methods, Gijsenij and Gevers [11] show in their results that by selecting the most appropriate algorithm, color constancy can be achieved with high accuracy.

2) Adaptation of the color space: this technique approach is focused not in the transformation over the pixels, but over the color model or the color classifier model. We will describe the methods that we found more related to a performance in real time in the RoboCup environment, but not necessarily work related to the same category of humanoids where the hardware limitation is really high. The first approach shown in [12] is very simple, they defined a base color and a bounding cube in the YUV color space to classify the base color (green for this work). Other colors are defined in relation to this cube. For example, sky-blue is defined as having a V value greater than the upper bound of the reference cube and a U value lower than the lower bound of the reference cube. With light changes, the positions of all colors move along the three axes and the intensities are amplified or weakened. But the relative position of the colors to each other remains. Thus it is sufficient to change position and dimensions of the reference cube with the lighting conditions. Another interesting approach is presented by Anzani in [13]. They use a known approach to color modeling, based on EM maximum-likelihood iterative estimation to translate and rotate the coordinates of the HSV color space according to the changes in the illumination. This known algorithm includes the possibility of stopping the EM-based adaptation; they adapted this algorithm to the multi-target domain required by Robocup real-robots league, especially for what concerns the stopping adaptation functionality; more important is the addition of on-line model order adaptation. Another example is presented in [14] where the authors introduce not an adaptation of an existing model, but a novel color space in which the associated metric approximates perceived distances and color displacements capture relationships that are robust to spectral changes in illumination.

C. Motivation

All the methods that we had mention so far, are post-acquisition process and due to the hardware limitations that we already presented, we can't make them work properly in combination with all the current tasks inside the robot. We came with the idea of trying to adjust the camera parameter *exposure time* to get the images as we need instead of making a software pre-processing of the images. This active calibration is achieved by a fuzzy logic system with very good results. We have to make notice that once we achieve the calibration parameters with the proposed method, there is no need of pre-processing the images for a color correction or adapting the color space we are using, so no extra time-consuming algorithm will be run as previous process of the main vision task in the robot.

III. COLOR SPACES AND SEGMENTATION

The segmentation is done by taking into account the following considerations: for HSV, minimum and maximum values are defined for hue, saturation and value in each color of interest. Similar considerations for the RGB color space are defined with minimum and maximum level of red, green and blue. In the YCrCb minimum and maximum values are defined for Y, Cr and Cb. If image values transformations are among the defined ranks of the minimum and maximum, these pixels are selected; otherwise their value are changed to black. With this we create three orthogonal axes in a three dimensional space where each color we want is a box that contains the pixels values belonging to it.

We made the segmentation in three different presentations of color spaces for compare differences in three different kinds of illumination. In figures 1, 2 and 3 we show a scene of the goal, the ball and the blue *landmark pole* which colors segmentation is shown in the three different color spaces: a)Shows segmentation in HSV, b)Shows segmentation in RGB and c)Shows segmentation in YCrCb. In Table I we see the comparison of segmentation for colors in RGB, HSV and YCrCb color spaces in the low-illumination level with respect to the average-illumination level images. Table II shows the comparisons of segmentation for colors in RGB, HSV and YCrCb color spaces in the more-illumination level with respect to the average-illumination level images.

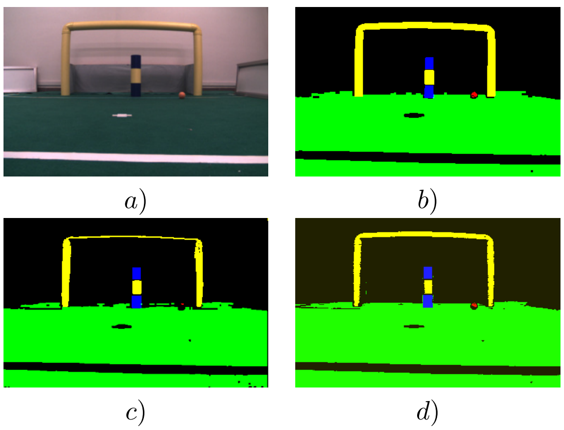


Fig. 1. Scene segmentation: a) full color, b) binary HSV and c) binary RGB , d) binary YCrCb

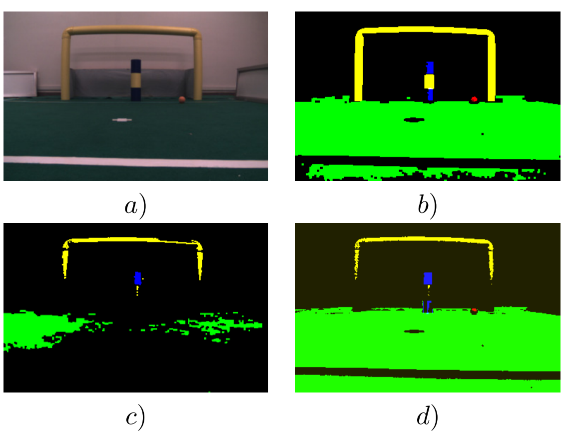


Fig. 2. Scene segmentation with less light: a) full color, b) binary HSV and c) binary RGB , d) binary YCrCb

The results show that in RGB color space the yellow color is strongly affected by illumination changes in comparison to HSV color space. The YCrCb color space is also very affected by illumination changes, but not as significantly as RGB. With these results, we selected the HSV color space because it will help the system for getting less iteration in our algorithm to get the exposure time needed.

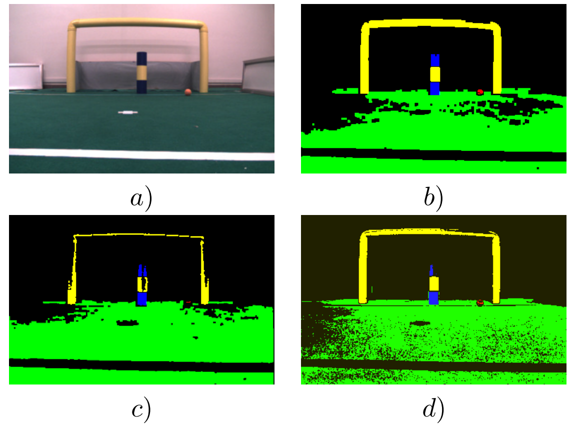


Fig. 3. Scene segmentation with more light: a) full color, b) binary HSV and c) binary RGB , d) binary YCrCb

TABLE I
SEGMENTATION DIFFERENCES BETWEEN COLOR SPACES WITH LESS ILLUMINATION

Color	HSV Diff.	RGB Diff.	YCrCb Diff.
Blue	20.56%	25.83%	38.22%
Yellow	7.58%	40.71%	53.66%
Orange	0.00%	100.00%	17.85%
Green	11.09%	83.689%	0.069%

TABLE II
SEGMENTATION DIFFERENCES BETWEEN COLOR SPACES WITH MORE ILLUMINATION

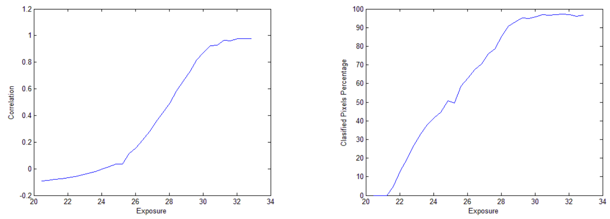
Color	HSV Diff.	RGB Diff.	YCrCb Diff.
Blue	4.67%	49.16%	33.11%
Yellow	4.33%	53.75%	8.61%
Orange	0.00%	0.00%	17.85%
Green	21.20%	9.36%	22.79%

IV. THE ACTIVE CALIBRATION

The active calibration consists in adjusting the camera parameters, which in our case, is carried out through the exposure time variation. This allows us to acquire the image according to our needs as opposed to the previous work described in section II-B, in which image adjustments were made after their acquisition. Since our method involves the adjustment of camera parameter comparing the changes in illumination, it is necessary to have a passive optimal segmentation at some light towards to try to approach at this as a response to illumination changes. In our experiment, we determined that the necessary correlation distance required to comply needs to be more than 0.6 in the range of [-1,1] and the percentage of correctly classified pixels, must be at least 95% to be considered satisfactory within the adjustments.

A. *Exposure time behavior model*

The exposure time model was based on the segmentation of one original image (base image) with certain exposure time. We made the passive calibration of the base image to classify our object of interest. After that, we vary the exposure time in the whole valid range to obtain the correlation and calculate the correctly classified pixels between the base image and the new image acquired with the new exposure time. Fig. 4 shows the relationship between exposure time and correlation coefficient(a) and the relationship between exposure and correctly classified pixels (b).



a) *b*)

Fig. 4. Exposure behavior: a) for correlation and b) for correctly classified pixels

B. Fuzzy membership functions and rules

We defined the membership functions as shown in Fig. 5, 6 and 7. Then, we define the rules of the exposure time behavior on Table III.

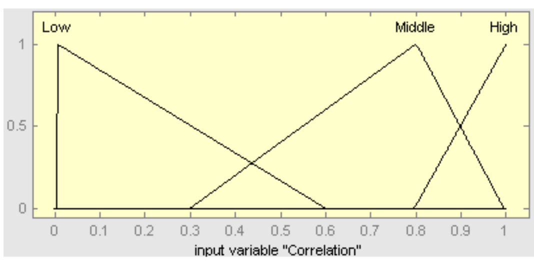


Fig. 5. Correlation between histograms

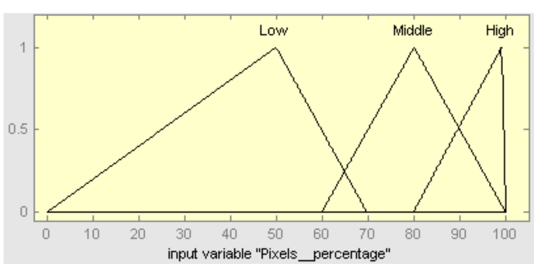


Fig. 6. Correctly classified pixels

TABLE III
FUZZY RULES WITH INPUTS: CORRELATION AND CORRECTLY CLASSIFIED PIXELS AND OUTPUT: EXPOSURE TIME

		Correlation		
		Low	Middle	High
Correctly classified pixels	Low	Short	Medium	-
	Middle	Short	Medium	-
	High	Long	Medium	Long

With these rules, we proceed to use the centroid method for defuzzification. We iterate the process having as input a new captured image with the new exposure time parameter until the difference between correctly classified pixels is lower than a threshold. For our tests, we iterate the process until 95% of pixels are correctly classified, having the algorithm iterated six times in the worst cases.

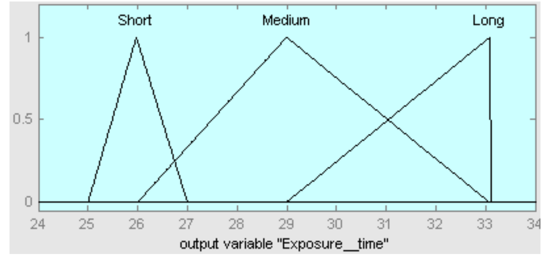


Fig. 7. Exposure time

V. CALIBRATION ALGORITHM

The steps for the passive calibration algorithm are as follows:

1) A frame is captured with the camera in a determined scene. Let us define this scene as *scene-A* which will be uses as base image (image-A) for the algorithm.
2) The color segmentation is made to *image-A* to find the HSV thresholds which are the ones that the robot will be using during the game.

Once we have done the passive calibration, the steps for the active calibration algorithm are as follows [1]:

1) A frame is captured with the camera in the *scene-A*.
2) The correlation is computed based on the brightness histogram of the new image and image-A.
3) The color segmentation is made automatically to the new image with the HSV thresholds previously introduced.
4) A comparison is made between the quantity of classified pixels in the new image based on the classified pixels in *image-A*.
5) If the result is at least 95%, the algorithm ends.
6) Else, the fuzzy system starts with the correlation distance, the percentage of classified pixels percentage and the current exposure time as inputs, giving the new exposure time as output.
7) The camera is set with the new exposure time and the algorithm continues to step 2.

Figure 8 shows the algorithm used to perform the active calibration.

VI. EXPERIMENTS

In order to test the effectiveness of the proposed methodology we did several experiments.

A. Experiment 1

Fig. 9 shows six test images taken with different illumination. The base image where the segmentation was made is presented in Fig. 10 (d) and exposure time is calculated to

[1]notice that this step is necessary only after a change in the illumination

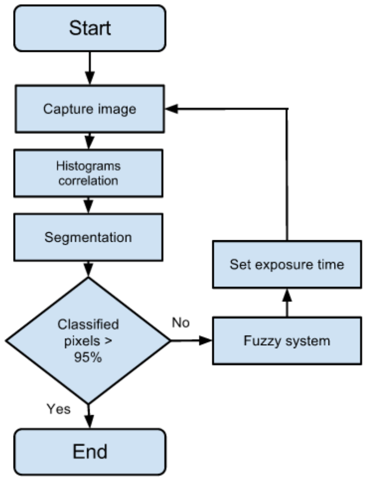


Fig. 8. Flow chart for the active calibration method.

respect the correctly classified pixels in the other images with the different illumination starting with a random number for the exposure time. Table IV shows the fuzzy system results for the exposure time of new images and the percentage of correctly classified pixels.

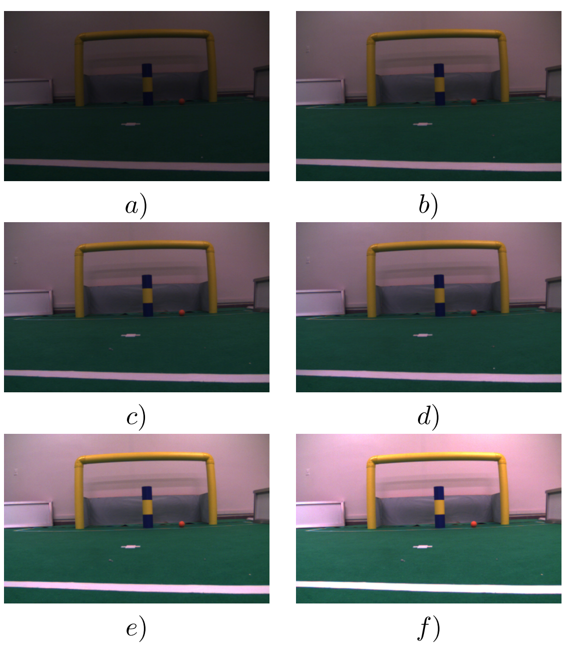


Fig. 9. Test images: from smallest amount of light (a) to highest amount of light (f)

In this experiment we didn't have errors with the threshold of 95% of correctly classified pixels.

B. Experiment 2

This experiment consists in taking a base image of a scene with the lab lights turned on or off depending on the case. Scene one is shown in Fig. 10 where the passive calibration is perform on image Fig. 10a. Image Fig. 10b shows the experimental conditions with lights turned on. The brightness

TABLE IV
RESULTS FROM EXPERIMENT 1

Figure	New exposure time (ms)	Correctly classified pixels
Fig. 9(a)	32.699	99.693%
Fig. 9(b)	33	99.877%
Fig. 9(c)	30.96	95.088%
Fig. 9(d)	32.247	99.326%
Fig. 9(e)	30.332	97.608%
Fig. 9(f)	25.992	95.994%

histograms[2] in Fig. 10c are computed for the base image (green bars) and the new acquired image (blue bars) from the camera the intersection of the histograms is colored in cyan. Then the proposed methodology is computed, new histograms are calculated for the new acquired images of the camera and when the correctly classified pixel percentage is at least 95%, the camera has been calibrated. The final histogram is shown with comparison to the base image histogram in Fig. 10d where we can see in cyan their intersection allowing us to see that the new images will be acquired within the same conditions of the base image so no new color calibration segmentation parameters of HSV color space will be needed. Scene two Fig. 11 and three scene Fig. 12 are tested in the same way as scene one.

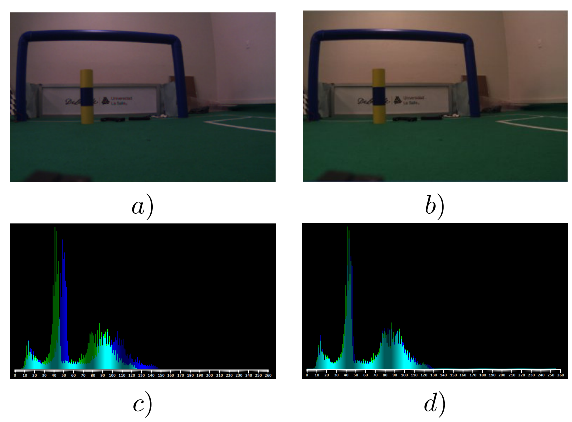


Fig. 10. Scene one: Blue color segmented, a)Base Image, b)Test Conditions, c)Image histograms, d)Image histograms after exposure time correction

TABLE V
RESULTS FROM EXPERIMENT 2

	Initial Distance	Final Distance	Pixel match
Scene 1	0.330	0.809	97.22
Scene 2	0.03	0.624	98.31
Scene 3	0.01	0.951	99.30

Table V shows the final results of experiment VI-B where the initial histogram distance is shown in the first column,

[2]based on the gray-scaled 8 bits depth image. Vertical axis represents the total of pixels for each value while the horizontal axis represents the brightness value in a range of [0,255]

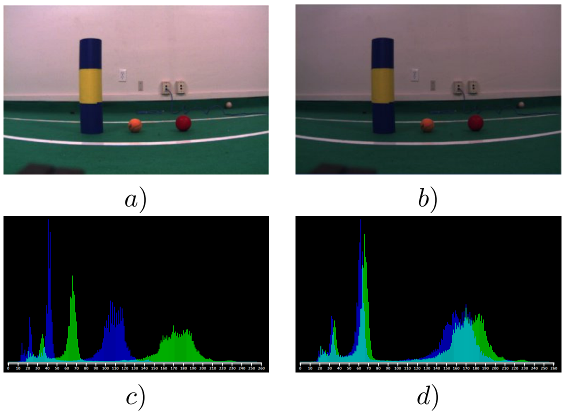


Fig. 11. Scene two: Orange color segmented, a)Base Image, b)Test Conditions, c)Image histograms, d)Image histograms after exposure time correction

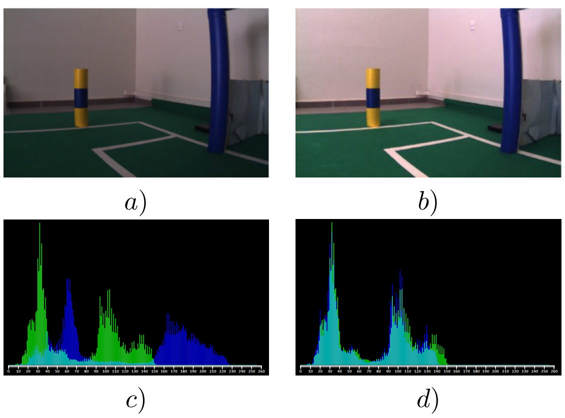


Fig. 12. Scene three: Yellow color segmented, a)Base Image, b)Test Conditions, c)Image histograms, d)Image histograms after exposure time correction

the final histogram is shown in the second column and the final correctly classified pixel percentage is shown in the third column.

VII. Conclusions and Future work

HSV format presents a big difference from the RGB and YCrCb format by providing the possibility of a more robust segmentation against illumination changes in the workplace. It was selected for the task because slight changes before illumination varies on average just under 15% in the number of correctly classified pixels. We introduce a fuzzy method to make an active calibration of the exposure time parameter. This method provides an adjustment of image source good enough and high-speed needed for a real-time task. With this adjustment methodology in substantial changes of illumination, we were able to adjust the image with a 95% of similarity between the base image segmentation and the final image set. For future work, we want to model another parameter of the camera: the Gain. This will allow us to work in more dark conditions, so we can expand our methodology to other tasks where light condition are really poor. We are currently extending this adjustment to work in the same way for the YCrCb color space since it has been requested to us for a commercial use in a system with web cams, using the YCrCb format.

VIII. Acknowledgments

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