Paper jc8-1-5

Dynamic Color Object Recognition Using Fuzzy Logic

Napoleon H. Reyes* **and Elmer P. Dadios****

*College of Computer Studies
2401 Taft Avenue, De La Salle University, Manila, 1004 Philippines
**Department of Manufacturing Engineering and Management
2401 Taft Avenue, De La Salle University, Manila, 1004 Philippines
E-mail: reyesn@dlsu.edu.ph
E-mail: reyesnap@yahoo.com
E-mail: dadiose@dlsu.edu.ph

[Received June 25, 2003; accepted September 9, 2003]

This paper presents a novel Logit-Logistic Fuzzy Color Constancy (LLFCC) algorithm and its variants for dynamic color object recognition. Contrary to existing color constancy algorithms, the proposed scheme focuses on manipulating a color locus depicting the colors of an object, and not stabilizing the whole image appearance per se. In this paper, a new set of adaptive contrast manipulation operators is introduced and utilized in conjunction with a fuzzy inference system. Moreover, a new perspective in extracting color descriptors of an object from the rg-chromaticity space is presented. Such color descriptors allow for the reduction of the effects of brightness/darkness and at the same time adhere to human perception of colors. The proposed scheme tremendously cuts processing time by simultaneously compensating for the effects of a multitude of factors that plague the scene of traversal, eliminating the need for image pre-processing steps. Experiment results attest to its robustness in scenes with multiple white light sources, spatially varying illumination intensities, varying object position, and presence of highlights.

Keywords: dynamic color object recognition, color constancy, contrast operators, Logit-Logistic Fuzzy Color Constancy Algorithm (LLFCC)

1. Introduction

Mimicking the human visual system's intrinsic object recognition capability is not quite an easy task in machine vision. The obscure features of color can only be ascribed to very vaguely, and the scene of traversal is plagued with a multitude of confounding imaging conditions for the vision system. Effects such as lighting and shadows, lens focus, and even quantum electrical effects in the sensor chip combine to make it essentially impossible to guarantee that the color being tracked down would remain constant as the object (mobile robot) traverses the exploration field. Suited to this kind of problem is Fuzzy Logic, a computational paradigm that is known to handle uncertainties very well. With its flexibility in its architecture to allow for description of control elements using vague linguistic terms, it efficiently lends itself amenable for handling the elusive features of color. However, despite all these promising capabilities, researches on fuzzy color processing are rather sparse. The full potential of Fuzzy Logic in the area of multi-channel color imaging is not yet fully explored. Apparently, its architecture is in dire need of additional support components for solving machine vision-related problems. It is in the light of this limitation that spawned the creation of the LLFCC algorithm, which attempts to extend the technique's computing prowess further in the realm of computer vision.

Most color constancy algorithms are primarily used for color balancing, and rarely have been actually put to use in a computer vision system like in a color object recognition task. Prominent color constancy algorithms such as Greyworld, White-Patch Retinex and 2D Neural Network [1] achieve color constancy by estimating the color of the incident illumination and then using that estimate to transform the image colors to canonical color descriptors. In addition, there also exist 2D and 3D-gamut constraint algorithms that can stabilize the appearance of an image by estimating the transformation directly [3]. Recent studies used the aforementioned color constancy algorithms in conjunction with image processing techniques like averaging of frames and image smoothing (e.g. using a 5x5 block) as pre-processing steps towards color object recognition. In particular, Funt et al. tested the color constancy algorithms along with color-indexing to recognize objects, but results show that they are not good enough for the task [3]. Similarly, Kwei et al. tested the same set of algorithms, except 2D and 3D gamut-constraints for the task of spotting colors of an object and consequently arrived with the same conclusions [5]. Nonetheless, it was observed that color constancy techniques does help improve the system's performance, but does not always guarantee good results. Existing color constancy algorithms may perform really well when the spotting task is for a particular color, but the same algorithm may perform poorly when spotting for another color.

Unlike existing color constancy researched which aim

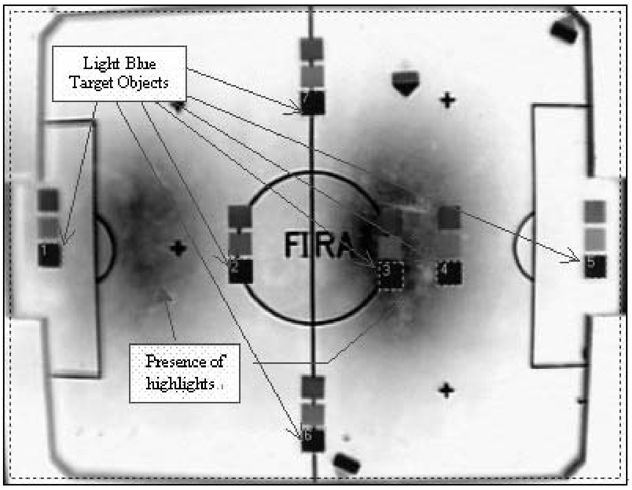

Fig. 1. Snapshot of the scene taken in a brightly-lit room (8 fluorescent lamps) confounded with highlights and similarly colored objects. Initial targets are 7 light blue objects marked with dashed lines and numbers. The colors of the image were inverted for clarity of printing.

to stabilize the image appearance per se, the proposed technique is geared towards achieving color constancy for explicitly pinpointing a target color object despite varying illumination intensities. Thus, a new term- *color locus constancy* is introduced to accompany the underlying principle behind the algorithm. To distinguish the new technique from existing ones, consider the von Kries model for example, which works by changing the gain of the three receptor cones in such a way that the cone responses are not altered by the illumination [9]. On the other hand, the proposed algorithm takes into account a color locus comprising of all the different shades of a particular color family depicting a single-color object by performing adaptive contrast operations on the color tristimulus to compensate for the effects of spatially varying illumination intensities, object position, rotation and presence of highlights. In effect, the term color locus constancy corresponds to the ability (which the vision system seek to attain) to stabilize a color locus depicting the colors of an object despite the complexity of confounding imaging conditions.

2. Dynamic Color Object Recognition Setup

The scene of traversal lies within the confines of a room illuminated by 8 fluorescent lamps, assembled by pair, with 4 of them directly on top of the exploratory field causing the two obvious oval-shaped highlights in the field as can be viewed in **Fig.1**. Target objects are characterized by single color patches (although multiple adjacent patches could also be used). The collection of patches investigated includes "similar" colors (see **Fig.1**) that closely resemble each other in terms of rg-Hue (Sec. 3.2). We believe that the real discriminating power of the technique can only be demonstrated when spotting for a target color despite the presence of other similar colors in the scene. In **Fig.1**, there are 3 shades of blue (i.e. light blue, blue and violet), with all light blue objects marked with dashed lines and tagged with numbers. The scene poses a relatively difficult task for the process of color spotting in that these color patches tend to appear almost the same under very dark or very bright illumination settings (as observed from experiments) To investigate the robustness of the algorithm under spatially varying illumination intensities, the objects were strategically scattered across the exploratory field under relatively bright, dim and dark regions. In **Fig.1**, objects 3 and 4 are located inside the oval-shaped highlights in the field, and so they are therefore under a relatively bright region in the exploratory field. On the other hand, objects 1 and 2 are near the highlights but missing it, consequently they fall under a relatively dim region. Lastly, objects 5, 6 and 7 are far from the highlights, accordingly they fall under a relatively dark region. In summary, the order of object illumination from brightest to darkest is: Target objects 3,4,1,2,7,6,5.

All images were acquired directly from the frame grabber's built-in video memory. No image pre-processing steps whatsoever (e.g. image smoothing, frame averaging) was performed on the images. Statistically, the test images used in this research are relatively more confounded with noise than in [5]. The standard deviation of the rg-chromaticities of the objects falls within the range [0.003-0.078], while in [5], the standard deviation was measured to be confined in a relatively very small range [0.001, 0.006], and so color discrimination for this research is relatively more difficult.

3. The Processes Involved for Dynamic Color Object Recognition

Basically, the dynamic color object recognition task can be described by the following steps:

1. Color classification via look-up table.
2. Blob construction / clustering of candidate pixels.
3. Object identification.

It is a necessary precursor for real-time object detection that a look-up table that maps all target colors be constructed. It is imperative that all confounding factors that impair the vision system be accounted for during the construction of the look-up-table. All processes involving mathematical rigors which entail long processing time could be employed during the construction stage, to ensure that color classification is done accurately. Consequently, candidate pixels are gathered into blobs; thereby isolating them from the rest of the surroundings for identification. A clustering technique described in [4] is used in this research which eventually leads to the final object recognition task. In the case of recognizing target objects comprising of multiple color patches, the relative proximity of the color clusters correlated to the color patches that make up the object is taken into account. For example, if robot 1 is characterized by light blue and pink patches, then the two closest clusters (based on the

Euclidean distance of their centroids) depicting the colors light blue and pink would correspond to robot 1.

Inevitably, once the vision system is in the active state, the entire object recognition process has to be accomplished at only a fraction of a second. In effect, in a fraction of a second, all three steps mentioned above have to be completed; without a color look-up table and the use of the window tracking technique (described in [4]), real-time detection would not be possible. The next succeeding discussions zero-in on the details of the color classification scheme which works in conjunction with adaptive contrast operations in generating the look-up table.

3.1. Color Contrast and Classification

Accurate color classification is vital to successful object recognition; an outline of the proposed color classification scheme used for the construction of the look-up table is described as follows.

1. Extraction of color descriptors.
2. Application of fuzzy contrast operations on each RGB channel (RGB -to- RGB_{new} transformation).
3. Extraction of color descriptors from RGB_{new} components.
4. Color classification.

Firstly, the proposed algorithm extracts color descriptors (Sec.3.2) from the original color tri-stimulus to determine which fuzzy contrast rules should be applied. Next, fuzzy rules adaptively perform contrast operations on the color tri-stimulus (Sec.3.4 & 3.5), transforming the original color tri-stimulus into contrast manipulated RGB components to account for all confounding imaging conditions. Different configurations and variations of the proposed fuzzy techniques were employed to control the application of contrast operations more efficiently, and such variants are discussed in Sec.3.6. Subsequently, color vectors are classified according to a pie-slice color decision region, which returns candidate pixels that are most likely to correspond to the target color object; the details of which are discussed in Sec.3.3. In the next succeeding subsections, details regarding the steps outlined are discussed separately in greater detail.

3.2. New Color Descriptors

A normalized RGB space called the rg-chromaticity model is exploited in this research. The color space is already known for its capability of reducing the effects of brightness [2], but to further extend its color discrimination potential, we introduce new color descriptors that enable separation of similar colors, and adhere to human perception of colors. The extraction of these color features are similar to what was described in [8], except that in this work, the rg-chromaticity space was exploited instead of the YUV color map. The idea is to define a new system of coordinates with its origin set at (0.333, 0.333), where the color white resides. In addition, the rg-color space is treated similar to an HSV model, which ascribes hue, saturation and intensity to a color. The new color descriptors, namely rg-Saturation and rg-Hue are derived as follows:

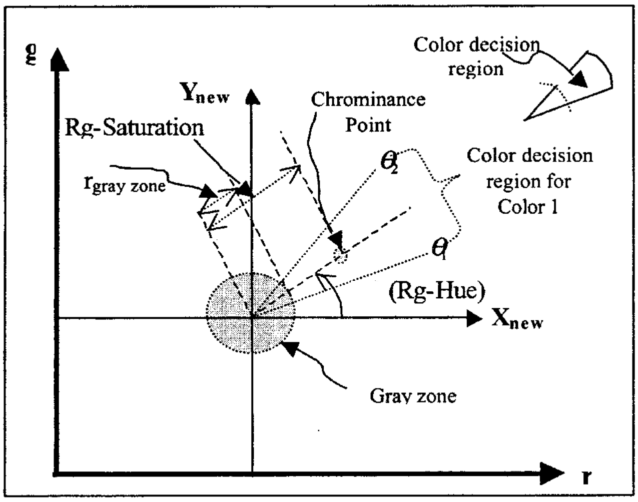

Fig. 2. Pie-slice color decision region in rg-color space.

1. Compute rg-chromaticities from the camera RGB tristimulus:

$$r = R / (R+G+B) \text{ and } g = G / (R + G + B) \quad (1)$$

2. Assign white as the new reference point or origin (O_{new}) of the new color space $O_{new}(0.333, 0.333)$, then compute for rg-Saturation as the radius extending from the origin to any given pair of rg-chromaticities.

$$rg \cdot Saturation = \sqrt{(r-0.333)^2 + (g-0.333)^2} \quad (2)$$

3. Next, compute for the rg-Hue descriptor as the angle relative to the X_{new}-axis of origin O_{new}:

$$rg \cdot Hue = \tan^{-1}((g-0.333)/(r-0.333)) \quad (3)$$

3.3. Pie-Slice Decision Region in Rg-Chromaticity Space

One of the challenges in color object recognition is the definition of a highly discriminating color decision region that can be easily customized by the user. Selecting a rectangular decision region inevitably envelopes neighboring colors, and so adjacent colors like pink and red for example would fall into the same color category. In [8], this problem has been drastically resolved; in a YUV-space, a pie-slice decision region that considerably helps reduce the effect of glare and hue drift was proposed. The same pie-slice decision region, excluding a gray zone (as depicted in **Fig.2**) is used in this research; however, characterized by rg-Hue and rg-Saturation in rg-chromaticity space. The idea is to utilize the ability of the rg-color space in reducing the effects of brightness, and combine it with the invariance of the pie-slice decision region to changing lighting conditions. **Fig.2** shows a more elaborate illustration of the proposed color descriptors. Color classification is performed in the new system

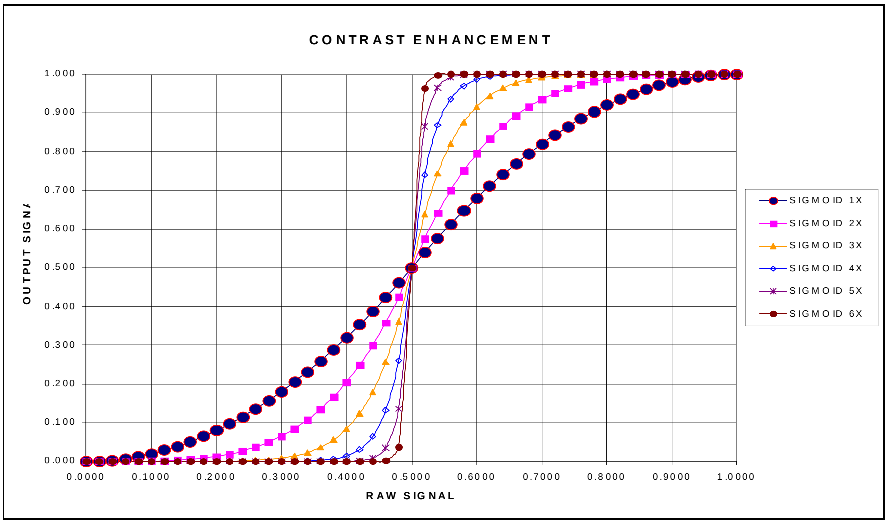

Fig. 3. Contrast Intensification operator.

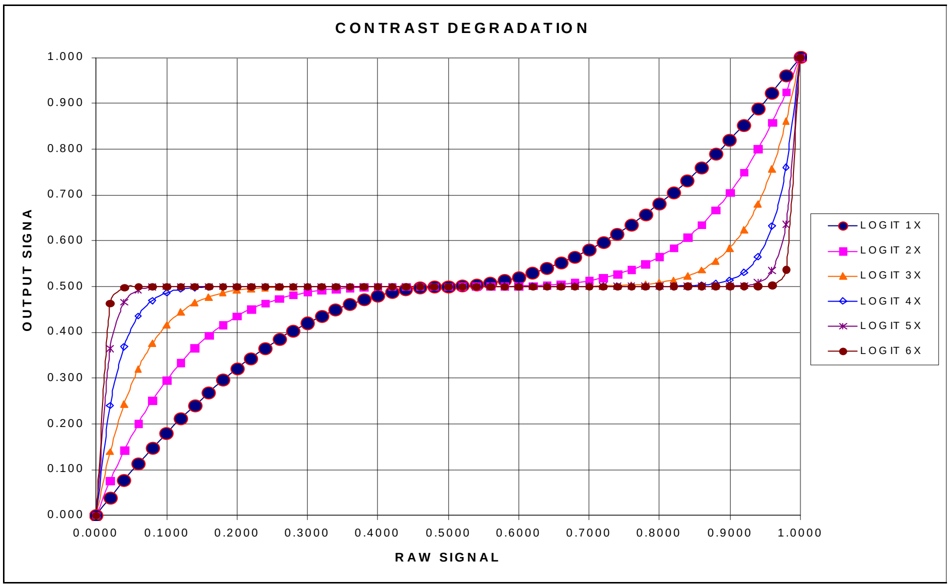

Fig. 4. Contrast degradation operator.

of coordinates bounded by the X_{new} and Y_{new} axes. Prior to executing the system for real-time detection, a look-up table is constructed, mapping all possible colors that can be encountered using a rule of the form:

If(*rg-Saturation* >= *r*) *and* (*rg-Hue* >= θ_1) *and* (*rg-Hue* <= θ_2)
Then*Color* = *1*. (4)

In adjusting the rg-Hue boundaries for the color decision region, it is worth-noting that adjustment requires precision of up to at least one decimal place.

In **Fig.2**, any given chrominance point, as described by its rg-Saturation and rg-Hue values, is mapped to its corresponding color decision region. A pie-slice decision region, excluding the gray zone is said to encompass effects of glare and hue drift [8].

3.4. Adaptive Contrast Operators

The proposed system utilizes a set of contrast manipulation operators, which act in a combination of contraction and dilation on the color vectors in order to account for the incessant shifting of the color locus due to all confounding imaging conditions. The two complementary operators employed in the system are as follows:

1. Contrast Intensification Operator (Logistic Function)

The graph in **Fig.3** shows how values are altered when contrast intensification is successively applied. The number of successive applications (r) of the operator is indicated as 1x, 2x , 3x, etc.

The contrast intensification equations below were taken in [7].

$$\alpha = \begin{cases} 2\mu_\alpha^2(y) & 0 \;\; \mu_\alpha(y) < 0.5 \\ 1 - 2[1-\mu_\alpha(y)]^2 & 0.5 < \mu_\alpha(y) \;\; 1 \end{cases} \qquad (5)$$

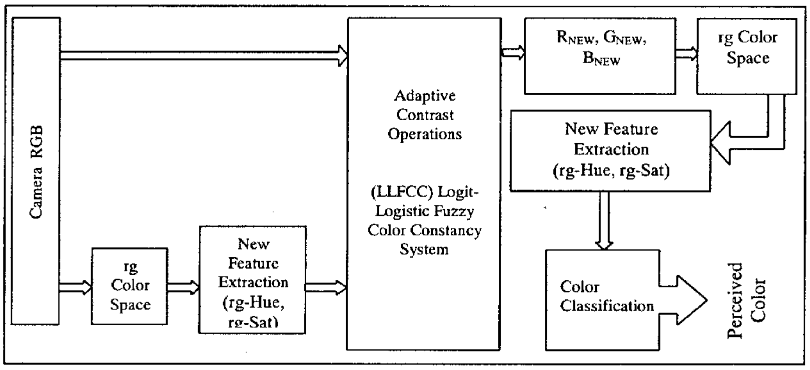

Fig. 5. General system architecture.

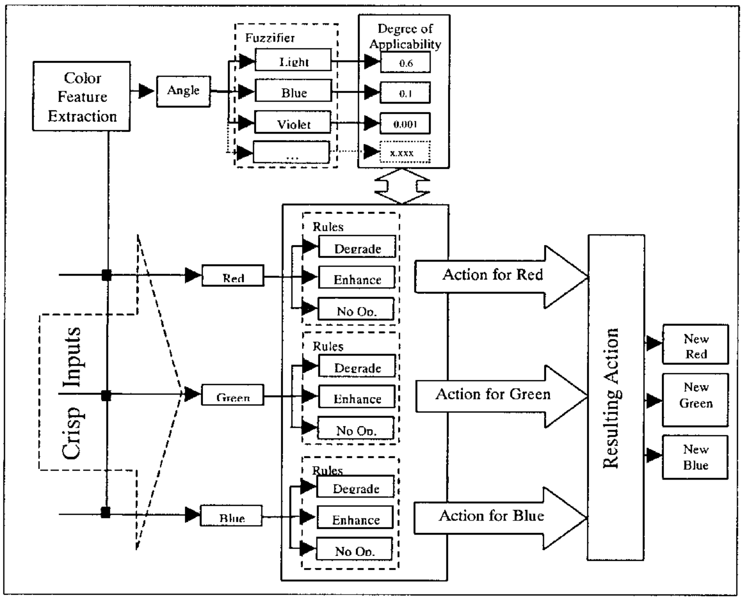

Fig. 6. Logit-Logistic Fuzzy Color Constancy (LLFCC) System: adaptive contrast operations.

where $\mu_{á}(y)$ is the raw input signal, and á the contrast manipulated signal. The threshold was fixed to 0.5.

If we let r represent the number of successive applications of the operator, then it can be observed that the slope of the curve gets steeper as r increases. Moreover, as r approaches infinity, the shape approaches a crisp (binary) function. Therefore, r can be set accordingly for domain-specific applications.

2. Contrast Degradation Operator (Logit Function)

In addition to the contrast intensification operator, a contrast degradation operator was originally derived, as shown in (5), in order to complete the set of contrast manipulation operators. The behavior of this operator takes the form of a logit function, and works by gradually contracting or concentrating signals towards the threshold setting of 0.5, thereby degrading contrast.

$$\alpha = \begin{cases} 0.5 + 2[\mu_\alpha(y) - 0.5]^2 & 0 \ \mu_\alpha(y) < 0.5 \\ 1 - (2[1 - [\mu_\alpha(y) + 0.5]]^2)] - 0.5 & 0.5 < \mu_\alpha(y) \ 1 \end{cases} \tag{6}$$

where $\mu_\alpha(y)$ is the raw input signal, and α the contrast manipulated signal. The threshold was fixed to 0.5.

Fig.4 shows how input signals are altered when contrast degradation is successively applied. The number of successive applications of the operator (r) is indicated as 1x, 2x , 3x, etc.

3.5. The LLFCC Algorithm

Fig.5 shows the overall architecture of the system. The LLFCC adaptively applies contrast operations to the color tristimulus. It operates by taking rg-Hue and rg-Saturation color descriptors (Sec.3.2), and employing the appropriate contrast rules on the RGB channels. The newly transformed RGB components are then converted to their corresponding rg-chromaticity values, and extracted of their rg-Hue and rg-Saturation values. Lastly, a color classification scheme (Sec. 3.3) determines the perceived color. Based on the experiments performed on actual scenes, the proposed system considerably accounted for the effects of all confounding imaging conditions that usually calls for extra image preprocessing

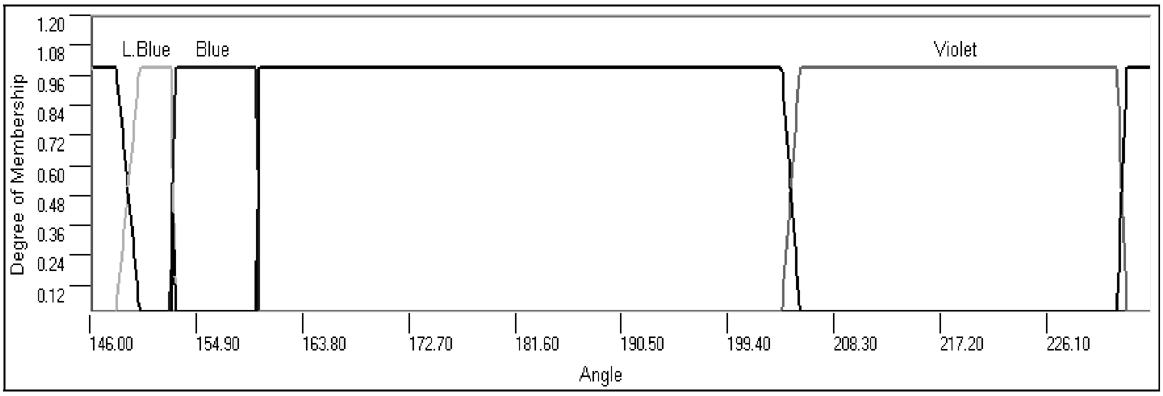

Fig. 7. Membership functions for light blue, blue, violet, and don ft cares fuzzy sets.

techniques (e.g. morphological operations, image smoothing, etc.).

In **Fig.6**, the LLFCC system that performs color locus constancy on the image via adaptive contrast operations is shown. For each RGB channel, there correspond fuzzy rules that perform contrast operations based on their degree of applicability. Trapezoidal membership functions which take the rg-Hue color descriptor as input return the degree of applicability of the rules. The rules in turn dictate which contrast operator to apply and by how much contrast should be applied to the color vectors. Rules act on either one of three possible ways on a color channel; that is, to degrade, enhance, or leave the RGB component as it is. The rules are tailored specifically for the target colors at hand. As an example, consider the following fuzzy contrast operation rule for light blue patches.

Sample Fuzzy Color Contrast Operation Rule:
If (rg-Hue depicts Light Blue) Then (Apply Low contrast Degrade on Red channel) and (Apply Low contrast Enhance on Green channel) and

(*Apply Low contrast Degrade on Blue channel*). (7)

The given fuzzy contrast rule in (6) applies to a color vector whose rg-Hue descriptor depicts Light Blue. If the antecedent is satisfied by the fuzzy membership function corresponding to Light Blue, then the Red channel is contrast degraded low, the Green channel contrast enhanced low, and the Blue channel contrast degraded low. Rules are derived based on the number of hits and misses that are returned when the RGB channels are contrast manipulated. The combination of contrast operations for each target color is empirically derived by testing all possible permutations of the contrast operations. The combination that returns the highest number of hits and lowest number of misses is considered the most appropriate rule for the target color at hand. During the construction of the look-up table, several rules could be triggered at any one time, and so the resulting action is then computed by fusing all rules that fired for each color channel.

Different configurations of the fuzzy system were considered to see effects of the following parameters on the accuracy of the system (other variants of the system are discussed in Sec. 3.6 more fully):

- Inclusion/exclusion of don't cares fuzzy color sets on each RGB channel.
- Restriction of the application of contrast operations; that is, whether to apply contrast operations on the entire image, or strictly on color vectors with rg-Hue values that are close to the target color at hand

The degree of applicability for don't cares fuzzy color sets is:

1 - Max. Degree of Applicability of All Rules Triggered. (8)

Fig.7 shows the complete mapping of fuzzy color membership functions for Light Blue, Blue, Violet and don't cares fuzzy color sets. In calibrating the parameters of the trapezoidal membership functions, it is worth noting that adjustments should be made precise up to at least one decimal place.

3.6. Variants of the LLS Fuzzy Color Locus Constancy Algorithm

In order to investigate how the proposed algorithm could be optimally configured, we have performed experiments on the following variants of the proposed algorithm:

1. **LLFCC1**- contrast operations are applied to the entire image based on rules that are tailored specifically for the target color. In this configuration, partial memberships on color sets are not allowed, and so only one rule is allowed to be triggered at any one time.
2. **LLFCC2 -** contrast operations are applied to the RGB channels of all pixels that fall within the boundaries of the rg-Hue constraints - set very close to the color decision region. In effect, the constraints would be a little less than θ_1 and a little greater than θ_2 (as shown in **Fig.2**). In this configuration, partial memberships on color sets are not allowed, and so only one rule is allowed to be triggered at any one time.
3. **LLFCC3 -** contrast operators are applied to the color tristimulus of the entire scene based on their degree of applicability, with or without considering don't cares fuzzy sets. (See Eqn.(8))

Table 1. Scope of parameters after calibration using sample actual images.

Color	Angle			Radius	Angle Contrast Constraints		Contrast Operation		
	Min	Max	Mean	Min	Min	Max	R	G	B
Light Blue	149.7	152.6	151.2	0.0289	148	153.1	degrade	enhance	degrade
Light Blue	151.6	153.1	152.4	0.0289	xxx	xxx	no op.	no op.	No op.
Blue	152.6	159.8	156.2	0.0370	150	161	degrade	enhance	degrade
Blue	150.5	155.4	153.0	0.0506	xxx	xxx	no op.	no op.	No op.
Violet	207.1	224.1	215.6	0.0542	xxx	xxx	no op.	no op.	No op.
Violet	205.5	232.1	218.8	0.0532	204.5	236.3	no op.	no op.	enhance

4. **LLFCC4 -** contrast operators are applied to the color tristimulus of all pixels that fall within the rg-Hue constraints set very close to the color decision region. Contrast manipulation is based on the degree of applicability returned by the fuzzy sets (with or without considering don't cares fuzzy sets).
5. **LLFCC5 -** contrast operators are applied to the color tristimulus of all pixels with degree of applicability < 0.72. Contrast manipulation is based on their degree of applicability, with or without considering don't cares fuzzy sets.
6. **LLFCC6 -** contrast operators are applied to the color tristimulus of all pixels that fall within the rg-Hue constraints set very close to the color decision region, and with degree of applicability < 0.72. Contrast manipulation is based on their degree of applicability, with or without considering don't cares fuzzy sets.

In gauging the performance of the system, the receiver operating characteristic (R.O.C.) proposed in [5] was utilized. Tables that depict true-positive (TP) proportions versus false-positive (FP) proportions are presented in the next section. The formulas used are as follows:

TP proportion = Hits / Pixels residing in ideal region (9)

FP proportion = Misses / Pixels outside the ideal region. (10)

where *Hits* correspond to pixels identified as representing the target color, and falls within the target region defined, while *Misses* correspond to misclassified pixels that are identified as representing the target color but falls outside the target region defined.

4. Discussion and Analysis of Results

Probing over a color locus formation depicting a particular target color object in rg-color space reveals that color locus shifting is prevalent as the object traverses the exploratory space under varying illumination intensities. In this undertaking, the ultimate challenge is not only to compensate for the effects of severe changes in lighting conditions, but to discriminate colors despite the presence of other similar colors in the scene as well. From the experiments performed, it was found that statistics does help in narrowing down the scope for rg-Hue values, but calibration is still necessary. An approximation is returned using the mean of rg-Hue for all lighting conditions $\pm$ std. deviation of rg-Hue for all lighting conditions (other approximations were tested, like taking the lowest among the minimum rg-Hue values and highest among the maximum rg-Hue values, but returned poor results). Having in mind the ubiquitous transformation of color locus depicting the target color, the primary objective is to account for those changes adaptively, while constricting the scope of parameters suited for the target color. After calibrating all parameters and testing on actual images, the values shown in **Table 1** were obtained.

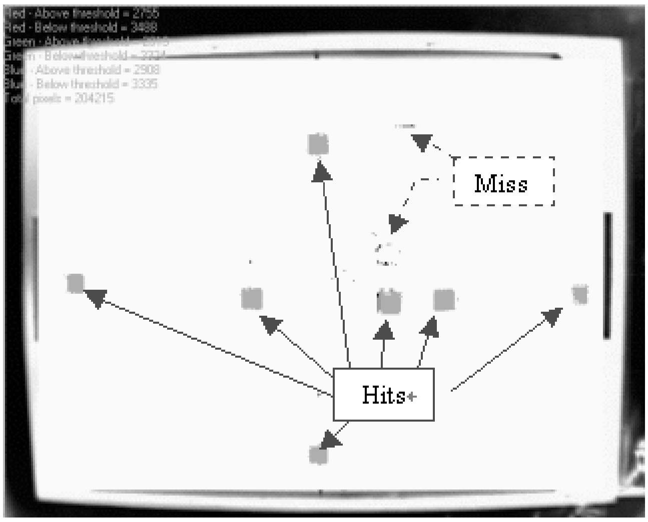

Fig. 8. Actual scene showing the effects of applying the fusion of contrast operations for detecting light blue patches. The colors of the image were inverted for clarity

Without contrast operations (for all RGB components with *no op.* settings in **Table 1**), setting the minimum rg-Saturation and boundaries for the rg-Hue alone would not suffice for accurate color spotting. Experiments were performed in finding the most appropriate rg-Saturation and rg-Hue combination so as to constrain color spotting solely on the light blue target color. Apparently, it was

Table 2. Performance of algorithms in spotting light blue at varying illumination.

Algorithm	Constrained Contrast	Don't Cares Fuzzy Sets	No. of Candidate Pixels	Hits	Misses	True Positives	False Positives	Rank
LLFCC1	N/A	N/A	2785	2294	491	0.651	0.0024	10
LLFCC2	Enabled	N/A	2301	2211	90	0.6274	0.0004	2
LLFCC3	Disabled	Disabled	2536	2282	254	0.6476	0.0013	9
LLFCC3	Disabled	Enabled	2505	2287	218	0.649	0.0011	7
LLFCC4	Enabled	Disabled	2301	2211	90	0.6274	0.0004	2
LLFCC4	Enabled	Enabled	2307	2214	93	0.6283	0.0005	5
LLFCC5	Disabled	Disabled	2482	2246	236	0.6373	0.0012	8
LLFCC5	Disabled	Enabled	2457	2253	204	0.6393	0.001	6
LLFCC6	Enabled	Disabled	2303	2213	90	0.628	0.0004	1
LLFCC6	Enabled	Enabled	2312	2217	95	0.6291	0.0005	4
No_Contrast	N/A	N/A	2800	2076	724	0.5891	0.0036	11
Ideal Region = 3524, Outside Ideal Region = 200691, Area = 204215, No. of Target Objects=7								

Table 3. Performance of algorithms in spotting blue at varying illumination.

Algorithm	Constrained Contrast	Don't Cares Fuzzy Sets	No. of Candidate Pixels	Hits	Misses	True Positives	False Positives	Rank
LLFCC1	N/A	N/A	2626	2238	388	0.6091	0.0019	5
LLFCC2	Enabled	N/A	1942	1835	107	0.4995	0.0005	1
LLFCC3	Disabled	Disabled	2184	1970	214	0.5362	0.0011	4
LLFCC3	Disabled	Enabled	2364	1986	378	0.5406	0.0019	6
LLFCC4	Enabled	Disabled	1942	1835	107	0.4995	0.0005	1
LLFCC4	Enabled	Enabled	1968	1852	116	0.5041	0.0006	3
LLFCC5	Disabled	Disabled	2985	2018	967	0.5493	0.0048	9
LLFCC5	Disabled	Enabled	3111	2043	1068	0.5561	0.0053	10
LLFCC6	Enabled	Disabled	2728	1878	850	0.5112	0.0042	8
LLFCC6	Enabled	Enabled	2691	1896	795	0.5161	0.004	7
No_Contrast	N/A	N/A	4223	1280	2943	0.3484	0.0147	11
Ideal Region=3674, Outside Ideal Region=200541, Area=204215, No. of Target Objects=8								

observed that the accuracy of color spotting without contrast operations couldn't get any better even after optimizing the values for rg-Hue and rg-Saturation to maximize the number of true positives and minimize the number of false positives. On the other hand, color spotting utilizing the synthesis of contrast operations successfully eradicated most of the extraneous pixels falsely representing the target color. As can be viewed in **Fig.8**, minimal extraneous pixels are reflected, while all target objects correctly classified.

Depicted in **Tables 2, 3** and **4** is the performance of the different variants of the proposed algorithm with adaptive contrast operations, as opposed to color spotting without using contrast operations. The choice of the top performing algorithm is determined by the measure of true positive proportion/false positive proportions, and appropriate rankings is shown (with 1 being the highest rank). As can be viewed in **Tables 2, 3** and **4**, color spotting without contrast operations is ranked the lowest among the algorithms in spotting for all target colors. On the other hand, applying contrast operations prior to color classification dramatically improved color spotting performance. However, different configurations ranked top in the three target colors. In spotting Light Blue color patches, based on the True Positive/False Positive proportions, LLFCC6 with don't cares fuzzy sets disabled gained the top spot. Next, in spotting Blue color patches, there are two top performing algorithms: LLFCC4 with don't cares fuzzy sets disabled, along with LLFCC2. Lastly, for recognizing Violet color patches, the best performing algorithm is LLFCC4 with don't cares fuzzy sets enabled. In the overall performance, it was observed that LLFCC4 with don't cares fuzzy sets enabled is the best configuration of the proposed algorithm for color spotting.

Table 4. Performance of algorithms in spotting violet at varying illumination.

Algorithm	Constrained Contrast	Don't Cares Fuzzy Sets	No. of Candidate Pixels	Hits	Misses	True Positives	False Positives	Rank
LLFCC1	N/A	N/A	3370	2413	957	0.7814	0.0048	6
LLFCC2	Enabled	N/A	3260	2361	899	0.7646	0.0045	3
LLFCC3	Disabled	Disabled	4249	2380	1869	0.7707	0.0093	10
LLFCC3	Disabled	Enabled	4144	2358	1786	0.7636	0.0089	8
LLFCC4	Enabled	Disabled	3257	2359	898	0.7639	0.0045	4
LLFCC4	Enabled	Enabled	3248	2353	895	0.762	0.0044	1
LLFCC5	Disabled	Disabled	4206	2385	1821	0.7723	0.0091	9
LLFCC5	Disabled	Enabled	4157	2366	1791	0.7662	0.0089	7
LLFCC6	Enabled	Disabled	3265	2363	902	0.7652	0.0045	2
LLFCC6	Enabled	Enabled	3256	2357	899	0.7633	0.0045	5
No_Contrast	N/A	N/A	3424	1805	1619	0.5845	0.008	11
Ideal Region=3088, Outside Ideal Region=201127, Area=204215, No. of Target Objects=7								

5. Conclusions

We have successfully developed and tested dynamic color object recognition techniques using a novel LLFCC architecture. Empirical results attest to its robustness under spatially varying illumination intensities, multiple light sources, varying object position and rotation, and presence of highlights. This research has successfully harnessed the potential of Fuzzy Logic in the realm of multi-channel color imaging by incorporating a new adaptive contrast operator. The techniques employed in this research is not limited to multi-channel color imaging, and thus, may very well serve its merits in other applications as well. We are currently working on enhancements to the proposed scheme by incorporating fuzzy color processing techniques discussed in [10].

Acknowledgment
The authors would like to acknowledge the support given by the De La Salle University -Manila for making this project possible.

References

1) K. Barnard, "Practical Color Constancy", Simon Fraser University, School of Computing Science, Burnaby, B.C. Canada, Ph.D. Thesis, 1999, available from ftp://fas.sfu.ca/pub/cs/theses/1999/KobusBarnardPhD.ps.gz.
2) G. D. Finlayson, B. Schiele and J. L. Crowley, "Using Color for Image Indexing", In The Challenge of Image Retrieval, 1998.
3) B. Funt, K. Barnard, and L. Martin, "Is Color Constancy Good Enough?", Proc. 5th European Conference on Computer Vision, pp. 445-459, 1998.
4) Kim Jong-Hwan, Robot Soccer System Manual, Intelligent Control Lab, KAIST, Korea, 2000.
5) G. Kwei, K. Barnard and B. Funt, "Spotting Colors," in Color Imaging Science--exploiting digital media, pp. 153-162, Lindsay W. MacDonald and M. Ronnier Luo, eds., John Wiley & Sons, 2002.
6) N. H. Reyes, E. P. Dadios, "Combining Fuzzy Techniques In Color Object Detection", In Proc. of First Humanoid, Nanotechnology, Information Technology, Communication and Control Environment and Management (HNICEM) International Conference, Manila, Philippines, March 27-30, 2003.
7) T. Ross, Fuzzy Logic with Engineering Applications. Singapore: McGraw-Hill, Inc., 1997.
8) P. J. Thomas, R. J. Stonier and P. J. Wolfs, "Robustness of Color Detection for Robot Soccer", Proceedings of the Seventh International Conference on Control, Automation, Robotics and Vision, ICARCV 2002, Singapore, on CD ISBN 981-04-7480-6, pp. 1245-1249, December, 2002.
9) H. Vaitkevicius, R. Stanikunas, "Color Constancy: A Simulation by Artificial Neural Nets", In Proceedings of the Seventeenth Annual Meeting of the International Society of Psychophysics, Pabst Science Publishers, 2001.
10) C. Vertan and V. Buzuloiu, "Fuzzy nonlinear filtering of color images: A survey", In E. Kerre and M. Nachtegael, editors, Fuzzy Techniques in Image Processing, Heidelberg, Germany, Physica Verlag, 2000.

Name:
Napoleon H. Reyes

Affilation
Ph.D. Computer Science student, De La Salle University (DLSU), Manila, Philippines

Address:
2401 Taft Avenue, De La Salle University, Manila, 1004 Philippines

Brief Biographical History:

1993- Received B.S. in Physics with Computer Applications, DLSU, Manila,
Phils.
1995-2000- Lecturer, Physics Department, DLSU, Manila, Philippines
1999- Received M.S. degree in Computer Science, DLSU, Manila, Philippines
2000-2003- Assistant Professor, Physics Department, DLSU, Manila, Philippines
Present - Full-time Ph.D. Computer Science student, DLSU, Manila, Phil-

Name:
Elmer P. Dadios, Ph.D.

Affilation
Full Professor - Department of Manufacturing Engineering and Management, De La Salle University, Manila, Philippines
Director - School of Engineering, De La Salle University, Canlubang, Philippines

Address:
2401 Taft Avenue, De La Salle University, Manila, 1004 Philippines

Brief Biographical History:

Finished Ph.D. (Department of Manufacturing Engineering) at Loughborough
University, United Kingdom

Main Works:

- He was a recipient of various awards among which were: Best Presentation at the 27th Annual Conference of the IEEE Industrial Electronics Society (Denver, USA, December 2001); IECON - 2000 Fellowship at the IEEE International Conference on Industrial Electronics, Control and Instrumentation (Nagoya, Japan, October 2000); Developing Countries Fellowship at the IEEE International Conference on Robotics and Automation (Nagoya, Japan, 1995); Miguel Febres Cordero Research Award (DLSU- Manila, Philippines, July 2000); Victor T. Lu Professional Chair of Manufacturing Process and Production (DLSU-Manila, 1996-1997); Thomas J. Lee Professorial Chair of the Manufacturing Engineering and Management (DLSU-Manila, 1997 to present); Exchange Scientist - Japan Society for the Promotion of Science (Tokyo Institute of Technology, Japan, 1997).
- He was the General Chair of the first International Conference of Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management 2003. He was also the Program Chair of the PICS-International Conference and Exhibition on Instrumentation and Control 2003.
- His research interests are: Robotics, Automation, Intelligent Systems, Neural Networks, Fuzzy Logic, Genetic Algorithms and Evolutionary Computations.

Membership in Learned Societies:

- Robautronix Corporation
- Federation of International Robot Soccer Association (FIRA)
- Philippine Instrumentation and Control Society (PICS)
- Computer Society of the Philippines
- IEEE
- IEE
- SME