Identifying Colour Objects with Fuzzy Colour Contrast Fusion

N. H. Reyes and C. H. Messom
Institute of Information and Mathematical Sciences,
Massey University, Auckland, New Zealand
{n.h.reyes, c.h.messom}@massey.ac.nz

Abstract

This paper presents further studies and improvements of a novel multi-channel Fuzzy colour contrast fusion algorithm for accurate colour object detection. Previous research tested the different architectures the colour contrast fusion algorithm may be built upon. Now, in order to test the generality of the algorithm, this research examines the algorithm's applicability in different colour spaces. The algorithm is able to capture the elusive features of colours depicting objects under spatially varying illumination intensities by adaptively employing a fusion of colour contrast manipulation operations in the form of fuzzy colour contrast rules. Unlike existing colour constancy algorithms, this algorithm selectively pinpoints the cluster of colours depicting the target object, and does not require stabilizing the colours of the whole image per se. Empirical results show that this algorithm is able to break the limits of accuracy of the pie-slice decision region for object colour spotting, using the robot soccer game as testbed. In all colour spaces tested, results show that the utilization of the algorithm always improves the accuracy of colour object detection. Furthermore, we also show that the algorithm succeeds in the task of selective object colour correction for improved colour object visibility under extreme lighting conditions.

1 Introduction

Colour cameras faithfully capture the colours of an object, as well as the colour of the source illuminant reflected on the object's surface. This however needs to be computationally accounted for, as an object's colour would change even with subtle changes in the environment. There's a myriad of confounding factors that plague the imaging system. Effects brought about by object rotation, lens focus, shadows, and even quantum electrical effects in the sensor chip combine altogether, making accurate colour object identification extremely difficult. Even when the camera and objects are set to be stationary, the colour tri-stimulus sensed by the camera would still vary to some degree. In contrast, the human visual system is able to compensate for illumination changes in the environment adaptively, instantaneously and effortlessly to keep the colours of an object stable. This fundamental characteristic of the human visual system, known as colour constancy, is desired for colour object recognition systems; however, the intricacies behind the phenomenon still remain to be discovered. In line with this, recent findings in the neurophysiological and neuropsychological research has shed some light onto this phenomenon, providing evidence that at low levels in the human visual system, there are mechanisms that mediate local chromatic contrast effects prior to image segmentation mechanisms [1]. Interestingly, the underlying colour contrast mechanisms involved in the algorithm presented here adhere to the general principles embraced by these findings.

It is worth noting that most colour constancy algorithms are primarily intended for colour balancing, and not for any vision-related task like object tracking. As a consequence, popular colour constancy algorithms such as Greyworld, White-Patch Retinex and 2D Neural Network did not perform consistently well when put into use for the object colour identification task [2, 3].

2 Experimental Setup

2.1 Colour Object Recognition System: Overview

The algorithms described here were tested for use in the robot soccer game, where each robot is identified by a collection of solid colour patches. Speed is vital in recognizing the robots in the game, preferably within a span of less than 33 msec [4]. The complete object recognition process requires colour classification, clustering of pixels or labeling, and robot identification, including the determination of robot position and orientation [4]. In this paper, our focus is on a multi-channel Fuzzy colour contrast fusion algorithm for improving the colour classification task in different colour spaces. Through the utilization of a colour look-up table and windowing techniques [4], the algorithm is well-suited for real-time colour object recognition [5, 6, 7].

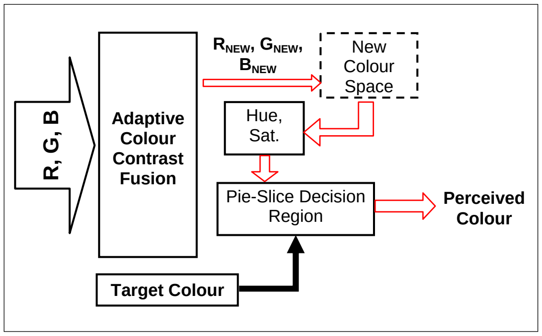

Figure 1: General System Architecture.

As part of a continuing research endeavor, we examine here the effects of applying the algorithm, in combination with a pie-slice decision region [4, 5, 6, 7, 8] in different colour spaces that are deemed to be more hue-separable than the transformed rg-chromaticity space [5, 6], such as the YUV and HSI colour spaces. For purposes of comparison, the accuracy of colour classification with or without colour contrast operations in different colour spaces was calculated in terms of true and false positive proportions.

2.2 Target Colour Objects Under Spatially Varying Illumination Intensity

The target colour objects in the experiments are simple solid colour patches. For relative ease in calibrating and measuring True and False positive proportions, which is performed pixel-wise, the patches were cut into small squares and distributed across the robot soccer platform in varying illumination intensities. Once all colour patches can be correctly spotted, several colour patches in different shapes and sizes can be used collectively to identify robots uniquely.

3 Colour Contrast Fusion Algorithm

After comparing the different architectures the colour contrast fusion algorithm may be built upon [5], it was observed that the general system architecture shown in Fig. 1 is the best choice in terms of speed and accuracy for colour identification. It is important however, to include R_{max} as an additional parameter in the pie-slice decision region to yield more accurate colour identification results.

Colours drift in the colour space as a result of changes in the illumination. To constrict the colour locus representing an object to some fixed pie-slice decision region, colour contrast operations are applied on each RGB channel. In Fig. 1, Adaptive Colour Contrast Fusion is employed first to account for all confounding imaging conditions.

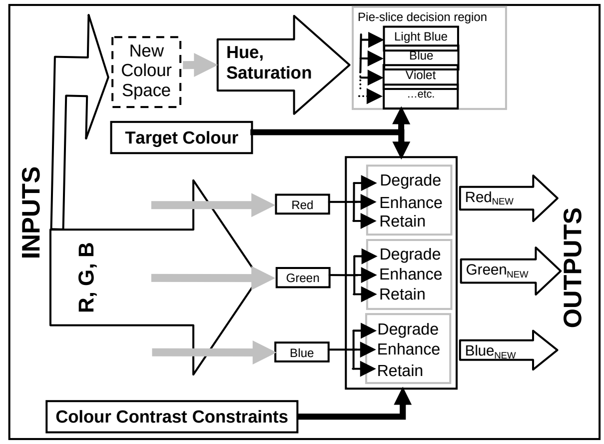

Figure 2: Adaptive Colour Contrast Fusion.

The adaptive colour Contrast fusion yields new colour contrasted values for R, G, B, which are transformed to a new colour space that would allow for the extraction of Hue and Saturation values, or Angle and Radius respectively. Lastly, a modified pie-slice decision region that incorporates a maximum radius parameter returns the perceived colour. This perceived colour is narrowed down to the number of predefined target colours specified in the system. If an object being tracked include Green, Pink and Blue colours for example, then the system would classify colours in the scene as to whether it belongs to the object (one of the object's colours), or not.

At the heart of the algorithm is the adaptive colour contrast fusion algorithm that employs either one of two complementary colour contrast operations; that is, either contrast enhance or contrast degrade; or, simply retain the original component's value(Fig. 2). These contrast operations are embodied in the colour contrast rules specifically tailored for the target object colour. From a predefined collection of colour contrast rules, along with their colour contrast constraints - which determines whether or not a colour pixel is supposed to be colour contrasted, and the given target colours at hand, colour contrast rules are triggered accordingly. Such contrast operations may be performed several times depending on the degree of illumination changes that affects the target colour at hand. Further details of the colour contrast operations are described in the following subsections.

3.1 Colour Contrast Operators

Two complementary colour contrast operators are used to compensate for hue and saturation drifting in a colour space due to the confounding factors that plague the imaging system. Colour contrast enhance was originally introduced in [9], and works with a combination of contraction and dilation of an input signal based on the threshold.

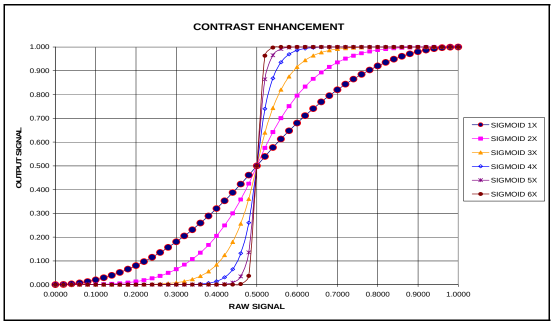

Figure 3: Colour Contrast Enhance Operator (Logistic Function/Sigmoid function).

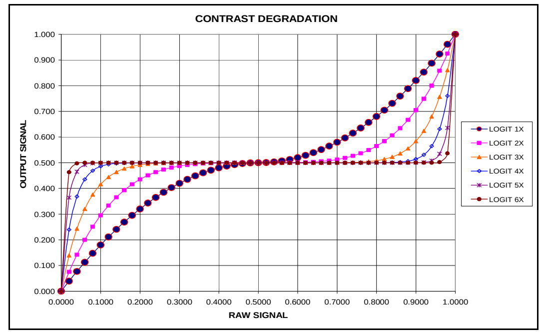

Figure 4: Colour Contrast Degrade Operator (Logit Function).

Any signal greater than or equal to the threshold will be amplified, while signals less than the threshold will be attenuated. On the other hand, colour contrast degrade is implemented by a Logit function that pulls any given signal closer towards the threshold setting; thereby degrading the colour signal.

Here, we employ the contrast operators independently on any RGB channel, at different degrees of application. For the task of colour object identification, experiments show that setting the threshold equal to 0.5 works extremely well. On the other hand, for colour correction purposes, the threshold may be moved accordingly.

Successive application of contrast enhancement or degradation causes the curve to become steeper. As can be viewed in the graph, the curve tends to appear more as a binary curve after 6 repetitive applications.

The equation for the logistic/sigmoid function is given in (1):

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

The equation for the logit function is given in (2):

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

3.2 Threshold Setting of the Colour Contrast Operators

Fig. 5 shows how the entire colour space is partitioned with reference to the threshold setting of the colour contrast operators. Specifically, in Fig. 5a), the black points denote colour pixels having normalized Red components with values greater than or equal to 0.5 (threshold). The remaining graphs shows what regions in the colour space denote High and Low for the Green and Blue channels, and how these regions would overlap.

The rg-chromaticity space has been well-known to be brightness invariant [10], although it is not very obvious from its triangular form that it allows for object colours to be separable using a pie-slice. To enable colour classification using a pie-slice decision region, the rg-chromaticity is transformed by moving its origin to where white resides. Consequently, the following extracted colour descriptors are used [5, 6]:

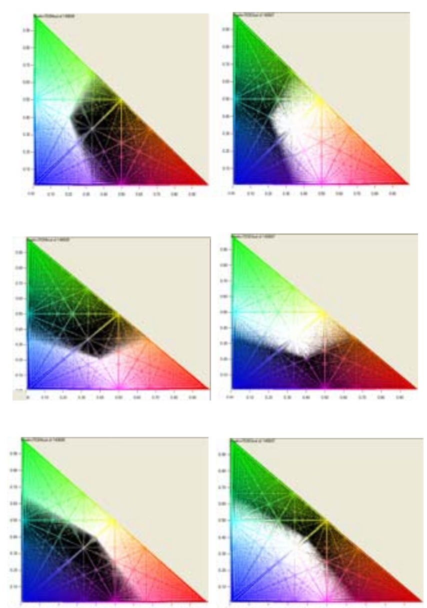

Figure 5: Colour Contrast Threshold Partitioning of the rg-chromaticity space (when threshold is set to 0.5).

a) Pixels above threshold: Red High; b) Pixels below threshold: Red Low; c) Pixels above threshold: Green High; d) Pixels below threshold: Green Low; e) Pixels above threshold: Blue High; f) Pixels below threshold: Blue Low

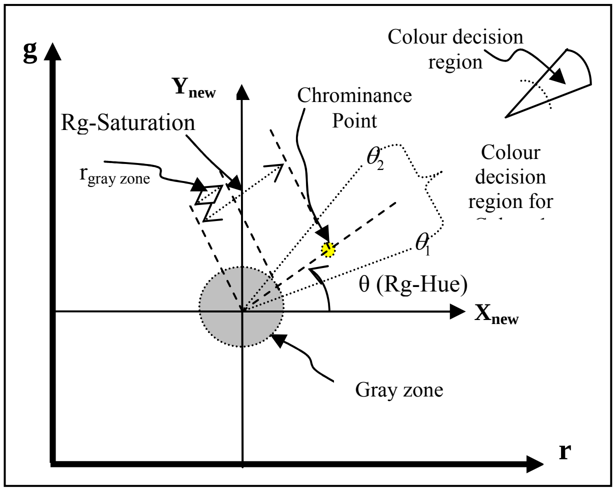

Figure 6: Transformed rg-chromaticity space.

1. rg-chromaticities
   $r = R / (R+G+B); \ g = G / (R + G + B).$ (3)

2. rg-Saturation (Radius)
   $$rg \cdot Saturation = \sqrt{(r - 0.333)^2 + (g - 0.333)^2} \qquad (4)$$

3. rg-Hue (Angle)
   $$rg \cdot Hue = \tan^{-1}((g - 0.333)/(r - 0.333)) \qquad (5)$$

3.3 Colour Contrast Rules

Colour contrast rules are empirically derived for each target colour. Colour contrast operations, and their level of application are determined for each colour channel, as shown below. Each colour channel may be colour contrast enhanced or degraded, at low, medium or high levels; or, simply retained as is.

If (rg-Hue depicts Light Blue) **Then**
(Apply High Contrast Degrade on Red channel) and (Apply Low Contrast Enhance on Green channel) and (Apply Medium Degrade on Blue Channel). (6)

Table 1 shows the colour contrast operation applied on each RGB colour channel, as well as the level of application of each operation. 'X' denotes no application of contrast.

3.4 Colour Descriptors

The following is a summary of all colour descriptors used for the colour pixel being examined and the target colour:

	Contrast Operation			R	G	B
RG SPACE	R	G	B	Level	Level	Level
Light Blue	Degrade	Enhance	Degrade	1	1	1
Blue	Degrade	Enhance	Degrade	1	1	1
Violet	Degrade	Degrade	Degrade	1	2	1
YUV SPACE						
Light Blue	Degrade	Enhance	Degrade	1	1	1
Blue	X	Enhance	Degrade	0	2	1
Violet	Enhance	X	X	3	0	0
HSI SPACE						
Light Blue	X	Enhance	Enhance	0	2	1
Blue	X	Enhance	Enhance	0	2	1
Violet	Degrade	Degrade	Degrade	1	2	2

Table 1. Colour Contrast Rules.

Descriptors for the Pixel being examined

- Hue (θ)
- Saturation (R)

Target Colour Descriptors

- Colour contrast rules (for R,G,B components)
- Level of Application for each colour contrast rule
- Hue constraints: $[\theta_1, \theta_2]$
- Saturation constraints: $[R_{min}, R_{max}]$
- Colour contrast constraints: $[\phi_1, \phi_2]$

The Target colour descriptors, as shown in Fig. 7, are empirically calibrated by simultaneously identifying several samples of the same target colour that are strategically placed under different illumination intensities.

For each colour pixel being identified, the following colour descriptors are examined (Fig. 6): the Angle (θ), which corresponds to Hue, or the general colour name in layman's terms (e.g. Pink, Violet, etc.), and the radius (R), which denotes Saturation, or the purity of the colour.

Colour contrast rules are triggered whenever the colour pixel being examined has a Hue value that falls within the bounds defined by the colour contrast constraints $[\phi_1, \phi_2]$. Otherwise, the colour pixel is classified immediately if it belongs to any of the target colours defined.

The application of the colour contrast fusion algorithm ensures that the colour is classified more accurately by compensating for the effects of illumination changes in the environment.

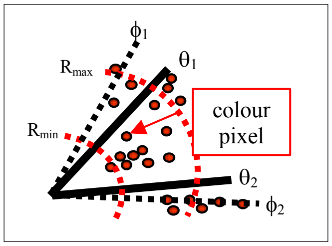

Figure 7: Target Colour Descriptors

	Angle		Radius		Contrast Constraints	
RG SPACE	Min	Max	Min	Max	Min	Max
LightBlue	149.688	152.604	0.0393	1	147.996	153.108
Blue	152.604	166.284	0.1326	0.4175	149.292	174.312
Violet	211.536	262.152	0.0765	0.1168	210.636	264.024
YUV SPACE						
LightBlue	283.284	289.044	10.476	55.71	276.912	296.496
Blue	277.164	317.088	45.288	136.422	269.712	324.936
Violet	327.384	360	35.676	75.15	319.032	338.688
HSI SPACE						
LightBlue	0	0.001	0.0589	0.2434	0	1
Blue	0	205.056	0.2621	0.9418	0	209.628
Violet	221.148	259.02	0.112	0.2763	220.68	260.856

Table 2. Colour Descriptors for the Target Colours.

Table 2 defines the colour descriptors used for each target colour.

4 Experiments and Analysis

4.1 Effects of Colour Contrast Fusion

In Fig. 8, with the presence of highlights caused by very bright illumination, a Green object tends to appear more as a whitish greenish object. This scenario is even more complicated by a nearby pale Yellow object, which appears to be very similar to the Green object, under the same illumination condition.

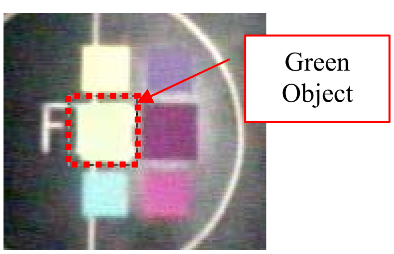

Figure 8: Green Object under bright white illumination.

In order to see how the colour contrast fusion algorithm influences the formation of the colour locus depicting the Green object to improve the colour classification task, we plot all the colours comprising the Green object, including some partial background colours (as marked by dashed lines in Fig. 8). The following diagrams illustrate which among the pixels are moved into, or out of the pie-slice decision region. Interestingly, some pixels were not significantly affected at all.

Fig. 9 shows the complete mapping of all colours residing within the selected area shown in Fig. 8. It can be observed that prior to colour contrast manipulations, the colours tend to cluster themselves close to the origin (location of white light).

Consequently, after the application of colour contrast rules, as shown in Fig. 10, the colour locus formation tends to be dispersed, separating the colours representing the object from any other colours not belonging to the object; therefore, allowing the colours representing the object to be identified through a pie-slice decision region. The effects of the fusion of contrast operations is shown in detail in Figs 11, 12 and 13, that shows which among the original colour pixels where moved into, out of the pie-slice, and which simply retained their positions in the colour space.

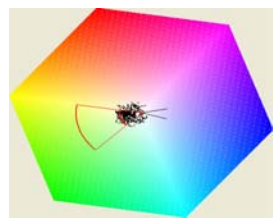
Figure 9: Colour Locus in YUV Space Representing Green Object with Partial Background Colours.

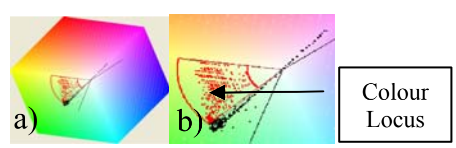

Figure 10: a) Colour Locus in YUV Space Representing Green Object with Partial Background Colours after the Application of Colour Contrast Fusion. b) Magnified version of the pixels in a).

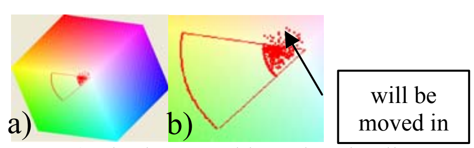

Figure 11: a) Pixels moved into the pie slice-decision region after colour contrast fusion. b) Magnified version of the pixels in a)

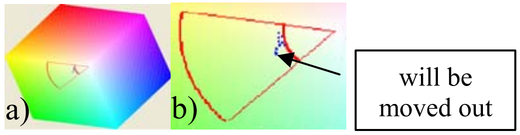

Figure 12: a) Pixels moved out of the pie slice-decision region after colour contrast fusion. b) Magnified version of the pixels in a)

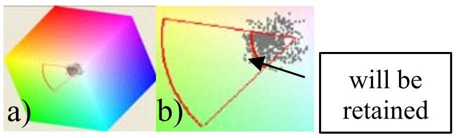

Figure 13: a) Pixels neither moved in nor out within the pie slice-decision region after colour contrast fusion. b) Magnified version of the pixels in a)

4.2 Limits of the Pie-Slice Decision Region

Fig. 14 illustrates the limits of the pie-slice decision region when identifying Light Blue objects in the HSI colour space. Calibration attempts to cut-down the number of false classifications by adjusting the boundaries for the angles and radius only reduce the number of correct classifications (Fig.14a). This problem is resolved only through the application of colour contrast fusion, significantly reducing the number of false classifications (Fig.14b).

4.3 Application of Colour Contrast Fusion in Different Colour Spaces

In the colour object identification results shown in the graph (Fig. 15), the colour descriptors were fine-tuned to ensure that 100% of objects targeted are correctly identified. This is achieved when at least 50% of the pixels in each target object is correctly classified.

The variations in true positive values in figure 15 are due to the variation in performance of the different colour spaces for different illumination of objects. A high true positive value indicates the method was good in some lighting conditions while poor in others, meaning that a high false positive rate is required to meet the 50% true positive identification limit per object in all lighting conditions.

The total true positive proportions over all objects as shown in Fig. 15 will be larger than 50% due to the minimum bound specified for each object. However, for the purpose of accuracy in identification, it is desired that the false positive proportions be minimal ensuring that they are not large and localized enough to be identified as one of the target objects.

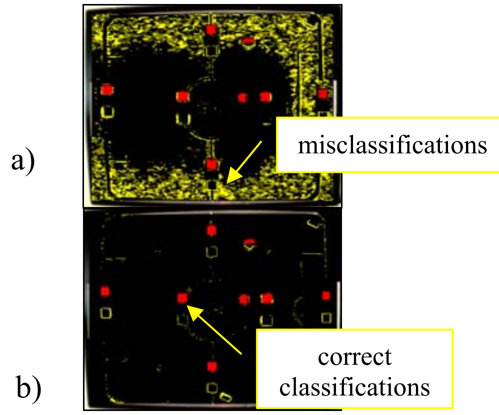

Figure 14: HSI Colour Space: a) Colour Identification with pie-slice decision region without colour contrast fusion; b) Pie-slice with Colour Contrast Fusion

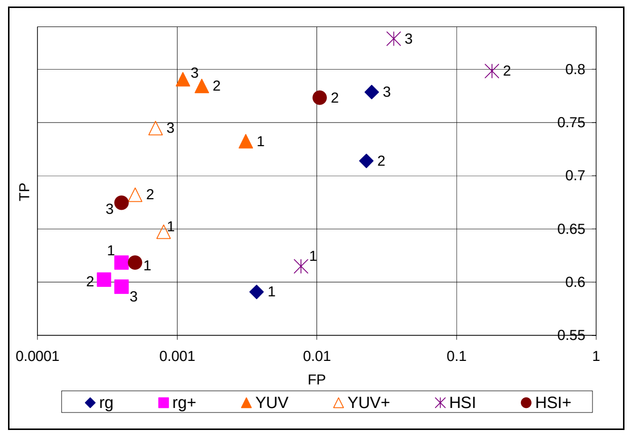

Figure 15: Results of Applying Colour Contrast Fusion in rg-chromaticity, YUV, and HSI Colour Spaces.

All labels with '+' sign indicate utilization of colour contrast fusion; absence of '+' indicates contrast operations not used. TP denotes True Positive proportions, while FP denotes False Positive proportions. All results guarantee 100% object identification. The graph depicts performance accuracy pixel-wise, with the x-axis scaled logarithmically.

	Light Blue		Blue		Violet	
Colour Space	**FP**	**TP**	**FP**	**TP**	**FP**	**TP**
Rg	0.0037	0.5908	0.0226	0.7139	0.0247	0.7786
Rg+	0.0004	0.6183	0.0003	0.6023	0.0004	0.5957
YUV	0.0031	0.7324	0.0015	0.7844	0.0011	0.7907
YUV+	0.0008	0.6473	0.0005	0.6821	0.0007	0.7447
HSI	0.0077	0.6149	0.1793	0.7984	0.0355	0.8288
HSI+	0.0005	0.6183	0.0105	0.7733	0.0004	0.6746

Table 3. False positive and true positive rates for the Colour Contrast Fusion Algorithm in rg-chromaticity, YUV, and HSI Colour Spaces.

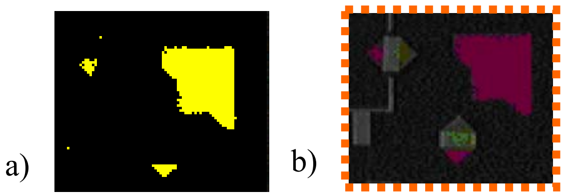

Figure 16: Results of projecting the new RGB values returned by the colour contrast fusion algorithm for Pink target colour objects under extremely dark illumination. a) Pixels classified as Pink. b) Colour corrected pixels.

As can be viewed in Fig. 15, the application of the colour contrast fusion technique improved the colour identification task in all colour spaces. It is also evident from the graph that the rg-chromaticity space best minimizes false positive returns, thereby allowing for more accurate colour classification. Table 3 provides the numeric equivalents of all the data plotting in Fig. 15. For each colour considered, the ranges for the radius, angle, and contrast constraints angle are optimally configured to ensure that all objects can be identified simultaneously at different illumination intensities.

4.4 Selective Object Colour Correction

Using the same colour contrast fusion algorithm for object colour identification, projecting the new RGB values returned by the algorithm shows that it helps in regaining the original colours of the object.

5 Conclusion

We conclude that the Colour Contrast Fusion algorithm improves colour object classification when employed in conjunction with the pie-slice decision region in the transformed rg-chromaticity, YUV and HSI colour spaces, especially under extreme lighting conditions. Further, it also proves to be useful for colour correction tasks.

Acknowledgements

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