

Quantitative Comparison of Color Systems for Robot Soccer Applications

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Abstract: Robot soccer has evolved into a very dynamic and competitive field within the last few years, many different robot soccer leagues now exist. Most of the leagues rely on computer vision in one form or another to gather information about the game situation – the position of a team's robots, the position of the opponent's robots and the ball. While some problems robot soccer vision posed have been solved in the last few years, many still exist. One of the most notable current problems is robot vision systems capable of coping with (potentially sudden) lighting changes. In this work, we will deal with one aspect of all vision systems that has a major impact on their performance: the choice of color system. This work aims at a quantitative comparison of color systems with focus on applications in robot soccer vision. We will evaluate the power of the color systems in question regarding color recognition and color discrimination as well as their behavior in changing lighting conditions.

1. INTRODUCTION

Robot soccer has evolved into a very dynamic and competitive field within the last few years. Many different robot soccer leagues now exist. Each of the two world-wide robot soccer associations – FIRA and RoboCup – has about five leagues which are evolving constantly. The scope ranges from truly tiny, centrally controlled wheeled robots in FIRA NaroSot (4.5 x 4.5 x 5 cm) to two-legged humanoid, fully autonomous robots in humanoid leagues (up to 180 cm in height). At the same time, the game play of the different leagues can be everywhere between highly autonomous and research-oriented to high-speed and entertainment-oriented (Kim et al, 2004).

Most of the leagues rely on computer vision in one form or another to gather information about the game situation – the position of a team's robots, the position of the opponent's robots and the ball. The arrangements regarding vision can be as diverse as the leagues themselves and range from global vision (supervision of the robots by stationary cameras) to local (i.e. on the robot), unidirectional and resource-restricted vision (Weiss, 2007).

While some problems robot soccer vision posed have been solved in the last few years (Weiss and Reusch, 2005), many still exist (Weiss, 2007). Most notable current problems are different (potentially unspecified) designs of fields or robot markings and relaxations of currently strict environmental conditions (most of all lighting conditions).

The last problem – robot vision systems capable of coping with potentially sudden lighting changes – is, as noted, a current major challenge in many leagues. In this work, we will deal with one aspect of all vision systems that has a major impact on their performance: the choice of color system.

As is well known, many color systems exist – ranging from hardware based systems like RGB and YUV over biology-

inspired systems like CIE XYZ to intuitive systems like HSI, HSV etc. Lately, the research focus has been on the CIE L*a*b* system (although it is now already over 30 years old), as major advances have been made on very practical and exact color difference metrics (CIEDE2000 (Luo, Cui and Rigg, 2001), although it is targeted at industrial applications) and some authors in robot soccer vision claim superior results of CIE L*a*b* over other color systems, e.g. the ones listed previously (see e.g. Umbaugh, 1999)

This work aims at a quantitative comparison of color systems with focus on applications in robot soccer vision. We will evaluate the power of the color systems in question based on a set of example pictures taken from one robot soccer league – FIRA MiroSot.

To do so, we will shortly introduce the FIRA MiroSot league and its vision setting in section 2. Section 3 will then present the methodology in detail. The results will be presented in section 4 and discussed in section 5. Section 6 shortly concludes the results, with section 7 listing possible future work.

2. SETTING

In the following, we will deal with the FIRA MiroSot league. In that league, the size of a robot is limited to 7.5 x 7.5 x 7.5 cm, which is very small considering the tasks it has to fulfill. The league started in 1996 with 3 vs. 3 robots playing on a field sized 150 x 130 cm. To get closer to “real” soccer, the number of players on the field slowly grew (5 vs. 5, 7 vs. 7) along with the field. It has now reached 11 vs. 11 robots on a 440 x 280 cm field and is therefore the first robot soccer league to physically play 11 vs. 11 games.

Over the years, games in that league have evolved into very dynamic, high-speed competitions with robots reaching speeds of up to 7.75 m/s (28 km/h) during game play. Alongside with

now refined strategies, this provides a very entertaining experience to spectators and big challenges to competitors.

Due to the very small size of the robots, they must be supported by a host computer (usually an off-the-shelf PC) which receives a picture of the field from two cameras mounted about 2.5 m above the field, each camera covering one half of the field. The host is responsible for image processing and strategic decisions. It transmits – via a radio link – movement information to the robots on the field, which they execute, thereby closing the control cycle.

Considering the high speeds of the robots, their small size and the size of the field, some of the general problems of MiroSot image processing systems should become clear immediately. The robots only cover 0.3 % of the visible image, and may travel 3 ½ times their own length between two pictures if a standard NTSC (30 frames/s) camera is being used. Processing is constrained by soft real-time conditions, meaning that one image has to be processed within approx. 20 ms on a standard PC (bearing in mind that the host PC is also responsible for strategy, GUI, and radio transmission processing).

Most of these problems have been satisfactorily solved in the last few years, some teams now use cameras delivering 120 frames/s, and successfully process all images delivered. Yet at the same time, this approach has led to rather inflexible vision systems (a remark that goes for other robot soccer leagues as well), that e.g. cannot cope with changes in environmental conditions like lighting changes at all or have only very limited ability to do so.

Regarding color models, the above approach has also led to the wide use of simple but “fast” models, mainly RGB and YUV, that lend themselves rather badly to precise color processing. So, future, better vision systems must turn towards other color models, which is why we have conducted a color system comparison specifically aimed at robot soccer, including ill-posed images.

3. METHODOLOGY

As a base for all considerations, we have produced a series of images of a FIRA MiroSot field with robot markings and a ball. The robot markings consist of sets of different color patches, every single patch being evenly colored. The image scenery has not been changed between images, but the environmental conditions (or in some cases the exposure parameters) have been modified to model changes a vision system might undergo in operation. See tables 1 and 2 for image property details and image excerpts.

When it comes to a comparison of color models, we are – in our field of application – mainly interested in their powers regarding color recognition and discrimination. Since we need to cope with changes in lighting, we also need to investigate their behavior in changing lighting conditions.

We will therefore separately investigate the following two topics:

- Static Inter-Patch Separability
- Dynamic Intra-group Changes

3.1 Static Inter-Patch Separability

We deal with a single image and choose a set of color patches from the image for further investigation. The main question here is the power of the color systems to separate the groups of colors from each other.

As a benchmark, we have calculated the normalized standard deviations (SDs) by group (i.e. single color group) and color components and the sum over color components (1). This number gives us an estimate of the compactness of the color groups, as compact representations are preferred for easier discrimination between groups.

$$sumsd (group) = \sum_{c=1}^3 sd (group, c) \quad (1)$$

with $sd (group, c)$ being the standard deviation of color dimension c of group $group$

Table 1: List of tests on single images (see section 3.1)

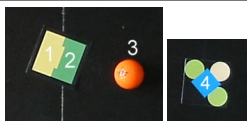
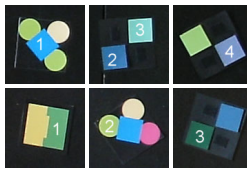
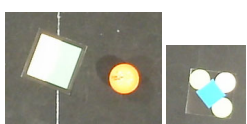
Test Number	Description	Test objective	Colors / Patches	Image Excerpts (Numbers superimposed)
1	Standard picture	Separability of distinctly different colors	Yellow, green, orange (Ball), blue patches	
2	Standard picture (same as in 1)	Separability of like colors	All blue and all green patches	
3	Strongly overexposed picture (overall, additionally strong light spots)	Separability of distinctly different colors	Yellow, green, orange (Ball), blue patches, additionally a white line and a spot interior	

Table 2: List of tests on multiple images (see section 3.2)

Test Number	Description	Test objective	Colors / Patches	Image Excepts (Numbers superimposed)
4 (listed as 4(1) and 4(2) in result tables)	Three pictures, intensity drop 1 Exposure Value (EV) between every picture	Behavior of color groups during EV changes	Yellow, green, orange (Ball), blue patches	
5	Two pictures, chromaticity change (camera white balance)	Behavior of color groups during white balance changes	Yellow, green, orange (Ball), blue patches	
6	Two pictures, physical lighting change between pictures (picture 1 neon, approx. 400 Lux on surfaces, picture 2 halogen spot lighting, between 475 Lux (outside spots) and 575 Lux (inside spots))	Behavior of color groups during physical lighting changes, affecting both intensity and chromaticity	Yellow, green, orange (Ball), blue patches	
7	One picture with external light sources (sun through windows), both very sunny (bright) and shady areas on the field (lighting intensity difference 1:5,3, 8000 Lux on the surface in sunlight, 1500 Lux in the shade)	Intra-Picture differences between strongly sunny and shady spots.	Yellow, green, blue patches	

The second benchmark is the mutual group center distances over all permutations of the groups, by color component. That distance is expressed in terms of summed standard deviations of the two groups involved, to give a result roughly comparable between color models, although it is dependent on the compactness of the color group's representation in that color system (2). (See below for a further elaboration).

$$distance\ in\ terms\ of\ sd\ (group1, group2, c) = \frac{|colorval_{group1,c} - colorval_{group2,c}| - sd(group1, c) - sd(group2, c)}{sd(group1, c) + sd(group2, c)}$$

for $(sd(group1, c) + sd(group2, c)) \neq 0$
 with $sd(group, c)$ being the standard deviation of color dimension c of group $group$,
 $colorval_{group,c}$ being the value of the color of dimension c of group $group$

As a comparison, the result tables also include normalized mutual group center distances.

3.2 Dynamic Intra-group Changes

We deal with two (sometimes three) images here and choose a set of different color patches from the images for further investigation. As the position of color patches has not been changed between the images, we can assess the changes of the patches' colors representation in various color models over the series of images and therefore make assumptions about the colors systems ability to represent color changes in a proper fashion.

As a benchmark, we take the movement of the groups (i.e. a patch's colors) between images. We calculate the absolute distance a color group has moved along one color component's axis as well as the euclidean distance. Results have been normalized. Preferably, lighting changes will cause movement in one axis' direction only (or at least predictable linear movement), as well as a small a movement as possible.

3.3 "Normalization", Reference of measurement

At this point, we must shortly discuss "normalization" in the sense we are using it here. When trying to compare different color spaces – and assess color distances within them – the common distance measure ultimately is the euclidean distance. (Neglecting the fact that much better distance measures are available for some spaces, ultimately influencing their performance.)

Unfortunately, while all color spaces in question are three-dimensional, the range a single color measurement can have in a given color space must not fit within a cube, or, differently put, the range of allowed values is not cubical (as it is in RGB) in all spaces. This leads to a major problem with regard to euclidean distances, as they are not comparable between color spaces. We decided to normalize all distances to a cubical space, having an allowed range of values of 0 to 100 along every axis. This means no change at all for a space like RGB (except for scaling, as RGB color values are usually expressed in terms of 0 to 1), but leads to compaction of some axes for other colors spaces (e.g. 1:4 compaction for CIE a* and b*).

Despite this fact, the resulting values may still serve as a rough estimate of distances in the color spaces, as they are now expressed as percentages of one color space axis. As we see in the results, the compaction does not seem to be a major issue, as uncompact axes (i.e. the shortest axis for all non-cubical systems) produce results in line with the results of compacted axes.

Despite this fact, we have also introduced measures in proportion to the sum of the standard deviations of the group's involved to facilitate better and more valid comparisons. They combine both relevant measures (standard deviation, distance) while abstracting from the actual form of the color model.

3.4 Color models

We will consider the following color systems: RGB, HSIp (polar version of HSI), CIE L*a*b* (whitepoint D50, LAB in the following for reading convenience) and LHC (polar version of L*a*b*, often denoted LCH). For comparison, we have sometimes also included YUV (which, as a linear transform, should perform similarly to RGB) and HSI (which should perform similarly to HSIp).

4. RESULTS

The full results of the evaluation are listed in tables 3 and 4. For test details, we again refer to tables 1 and 2.

We will present the significant results by benchmark as ordered in section 3.

4.1 Static Inter-Patch Separability (Tests 1-3): Standard Deviations

Obviously, small standard deviations (SDs) are preferred here, as they indicate a compact representation of a color group within a color space.

Looking at the values over all (both single values and group's sums), RGB has the highest SDs by far. YUV performs significantly better, HSIp roughly compares to that performance. LAB performs again significantly better, with LHC being comparable to LAB.

We need to comment in detail on some results in test 3, as at a first glance, they seem to contradict the above. Quite a few standard deviations are listed as 0 here (especially for RGB), yet this does not mean a good performance. The image is very ill-posed (cf table 1, test 3), and RGB particularly reaches its discriminatory power here, as the actual color values (not listed) show. For groups 1 and 2, all color values are very close to 100 (full value). That means that the colors are very close together, the representation is so compact that green and yellow cannot be reasonably separated.

LAB and LHC perform outstandingly better, they present non-zero SDs in all groups and components. A look at the actual values confirms that the discriminatory power – especially of LHC's H-component – is far greater. (H group 1: 11, group 2: 34). As drawback, LHC sometimes produces very large SDs in its H-components (above example: 20 for both groups).

Interestingly, LAB performs better here, e.g. a* for this example: group 1: 49,98, group 2: 49,36; SD group 1: 0,03, group 2: 0,09).

Regarding HSI and HSIp, HSIp performs as poorly as RGB, with HSI performing slightly better.

4.2 Static Inter-Patch Separability (Tests 1-3): Mutual Group Center Distance

If we look at the normalized mutual group center distances for tests 1 and 2, the distances are largest for RGB, about half these distances for YUV and HSIp, and again half for LAB and LHC. The results in test 3 (the ill-posed image) look different: The smallest distances occur in HSIp and LAB, double the distances in RGB, which HSI and LHC having greater distances by far.

As we have stated in 3.3, actual distances, although normalized, might mislead here, so we now have a look at mutual group center distances expressed in terms of the groups' SDs sums. The results look somewhat different here, overall all systems perform similarly in tests 1 and 2. Test 3 then differentiates the systems, as here RGB mostly does not have to power to separate colors, as discussed above. Only LAB and LHC do not have zero SD sums (“SD0”) and manage to separate all groups from each other (at least one color component center distance must be positive to do so). One exception is the separation of groups 3 and 4 (second part of the test), which only YUV manages. Yet these groups are a white line on the field and a very bright light spot on the field, so separation is not an actual issue here.

Otherwise, LHC and LAB perform very similarly, with a very slight advantage on LAB's side.

4.3 Dynamic Intra-group Changes (Test 4-7)

Regarding a color system's dynamics, we are interested in as small a movement as possible (small euclidean distance) as well as predictable movement, preferably along one axis only.

If we look at the euclidean distances first, we find that RGB performs worst in all tests. HSI follows next, usually having half the distance of RGB. LAB and LHC have about a third of the RGB distance, and perform very similarly, with small advantages on the side of LAB. HSIp performs similarly to HSI, possibly slightly better.

If we look at the movement by color axis, we should take into account what conditions we have changed in specific tests.

In test 4, we have changed the lighting intensity only (by changing the exposure value). Especially with systems separating intensity from color information, we prefer to find movement along the intensity axis only (HSI/HSIp: I; LAB/LHC: L*). For test 4(1) (EV drop of 1) this is not the case, although we can find a tendency for I/L*-values being larger than the other components, yet these are not close to zero. In test 4(2) (another EV drop of 1) this becomes clearer, as the I values change much stronger than H/S. The result is not as clear for LAB/LHC: Although we can see a dominance

Table 3: Results of Tests 1-3 (Static Inter-Patch Separability)

Test	Color groups	Color system (C1/C2/C3)	Standard Deviations (normalized to 0..100 cubical spaces)												Sum of normalized Standard Deviations over Colors								Mutual Group Center distances (normalized to 0..100 cubical spaces)											
			Group 1			Group 2			Group 3			Group 4			Group 1	Group 2	Group 3	Group 4	Group 1 -				Group 2 -				Group 3 -							
			C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3					Group 2	Group 3	Group 4	Group 2	Group 3	Group 4	Group 3	Group 4	Group 3	Group 4						
1 (Standard picture)	1 - Yellow	RGB	3,74	4,24	6,08	4,12	2,83	3,87	15,36	21,73	18,65	2,83	1,73	2,83	14,07	10,82	55,74	7,39	51,53	42,45	87,87	63,78	55,19	112,98										
	2 - Green	YUV	4,24	2,83	0,71	3,00	1,00	1,43	18,44	4,80	5,89	1,41	1,00	1,60	7,79	5,43	29,13	4,01	29,95	33,38	53,84	36,06	30,05	61,85										
	3 - Orange (Ball)	HSB	3,87	1,32	4,47	1,58	2,74	3,16	7,21	4,27	17,03	2,06	0,87	1,41	9,67	7,48	28,51	4,34	30,37	31,93	53,38	39,04	33,74	69,11										
	4 - Blue	LAB	1,81	0,22	0,80	1,40	0,82	0,53	13,12	4,11	7,01	0,80	0,64	0,40	2,83	2,76	24,23	1,84	11,88	20,62	20,73	21,39	12,23	29,13										
		LHC	1,81	0,58	1,28	1,40	1,05	1,31	13,12	2,52	12,45	0,80	0,57	1,05	3,67	3,77	28,09	2,41	17,14	21,67	36,56	29,60	20,24	44,65										

Test	Color groups	Color system (C1/C2/C3)	Mutual group center distances (in terms of group's SDs sum)																							
			Group 2			Group 3 -			Group 4			Group 3			Group 2 -			Group 4			Group 3 -			Over all groups		
			C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	Smallest	Largest	
1 (Standard picture)	1 - Yellow	RGB	5,13	1,29	-0,15	-0,98	0,60	0,70	10,58	2,40	3,38	1,45	0,04	0,50	3,01	-0,09	6,08	3,16	-0,09	2,78	-0,98	10,58				
	2 - Green	YUV	2,43	1,11	5,83	0,29	-0,17	1,75	4,34	7,90	11,43	-0,79	1,48	3,48	0,22	12,00	3,66	-0,96	5,96	5,26	-0,96	12,00				
	3 - Orange (Ball)	HSB	2,29	-0,18	2,18	0,87	-0,96	0,30	6,20	10,73	2,25	3,40	-0,49	-0,81	5,80	5,20	0,12	5,84	4,04	-0,52	-0,96	10,73				
	4 - Blue	LAB	2,12	4,74	0,67	0,25	0,96	0,40	4,44	6,34	10,48	-0,41	1,94	0,75	0,89	-0,76	11,38	-0,68	1,12	2,33	-0,76	11,38				
		LHC	2,12	7,21	0,50	0,25	2,33	0,41	4,44	27,64	2,53	-0,41	5,62	0,13	0,89	10,95	0,84	-0,68	12,92	-0,17	-0,68	27,64				

Notes:

- "SD0" denotes that the sum of the standard deviations of both groups involved is zero, and (2) is not defined.
- Negative mutual group center distances in terms of group's SD sums mean that the groups overlap if the SDs are considered.

Table 4: Results of Tests 4-7 (Static Inter-Patch Separability)

Test	Color groups	Color system (C1/C2/C3)	Movement (normalized to 0..100 cubical spaces)																												
			Group 1				Group 2				Group 3				Group 4				Group 1				Group 2				Group 3				Group 4
			Along	Along	Along	Euclidean	Along	Along	Along	Euclidean	Along	Along	Along	Euclidean	Along	Along	Along	Euclidean	Along	Along	Along	Euclidean	Along	Along	Along	Euclidean					
			C1	C2	C3	Distance	C1	C2	C3	Distance	C1	C2	C3	Distance	C1	C2	C3	Distance	C1	C2	C3	Distance	C1	C2	C3	Distance					
4(1) (Intensity drop 1 EV between pictures, picture 1 0 EV, picture 2 -1 EV)	1 - Yellow	RGB	0,74	2,9	21,28	21,49	21,98	16,04	20,43	34,03	0,28	25,98	20,19	32,9	19,77	19,71	0,04	27,92													
	2 - Green	HSB	5,68	7,96	8,31	12,83	1,87	1,91	19,48	19,66	11,4	2,51	15,48	19,39	4,95	8,52	13,17	16,45													
	3 - Orange (Ball)	LAB	3,06	0,99	3,46	4,72	7,27	1,84	1,08	7,58	9,99	4,91	3,07	11,55	9,14	0,67	3,88	9,95													
	4 - Blue	LHC	1,06	2,85	5,73	6,49	7,27	0,73	3,4	8,06	9,99	6,2	5,74	13,09	9,14	7,52	2,8	12,16													

of L^* over a^*b^*/HC , the performance is not as good as in HSI. (see test 4(2), group 3, LAB/LHC C1 vs C3).

Looking at test 5 (white balance change) RGB gives us a strong clue that the white balance has mainly changed the blue component, as most change is in B only. The change in HSIp is distributed over all components (including I). The change in LAB/LHC is mainly in a^*b^*/HC , as could be expected, and is much stronger in b^* than a^* , as is also expected.

Test 6 does not give us many result not already stated. It should be noted that for a strong external change (neon lighting vs 4 halogen spots), the overall changes are remarkably small, especially for HSIp, LAB and LHC.

Test 7 presents us a picture that could be called a benchmark picture for vision systems, as it has strong intra-picture color differences. The intensity changes cause strong movements in RGB space in all components. HSI and HSIp manage to concentrate the change mainly in the I components, albeit some stronger changes occur in other components as well, though with I changes at least 4 times stronger. The performance of LAB/LHC could be called remarkable, if it weren't for strong changes in b^*/C in group 1, with the C change being as strong as the L change. Otherwise, the overall distances are remarkably low for such an ill-posed picture, and colorness changes are quite small.

5. DISCUSSION

5.1 Static Inter-Patch Separability (Tests 1-3)

Most results are not unexpected: LHC/LAB give much more compact representations of color groups than HSI, which is in turn outperformed by LAB/LCH. Somewhat surprisingly, YUV performs much better than RGB here.

When we look at a very ill-posed picture (test 3), we get much clearer – and again not unexpected – results. RGB clearly reaches its limits here and could not perform recognition in a vision system, the same being true for HSI and HSIp. Only LAB and LHC stand a chance of actually presenting enough separation power for recognition. It should be noted that LHC also shows drawbacks here, as the SDs of H are occasionally unacceptably high. Overall, LAB is the only system performing fully satisfactorily – within the strong limitations the picture itself poses – in this test.

The reflections on mutual group center distance follow the above and support the conclusions.

5.2 Dynamic Intra-group Changes (Test 4-7)

Again, the overall results by color systems are not surprising, RGB having the strongest movement (largest distances), followed by HSI/HSIp, and outperformed by LHC/LAB.

Regarding artificial intensity changes (test 4), HSI/HSIp outperform LAB/LHC in separating intensity from color, yet this levels out in real intensity (lighting) changes (test 6).

On the other hand, LAB/LHC manage artificial color changes (test 5) much better than HSIp.

Test 7, the ill-posed picture, presents us with the rather remarkable finding that HSI/HSIp manage more even performance than LUV/LAB, which have some unsatisfactorily results. On the other hand, the movement in HSI/HSIp is overall bigger, yet without doubt more even.

6. CONCLUSION

First of all, we have not evaluated all systems in all cases, and the first finding is that YUV can perform better than RGB, and HSI and HSIp also perform differently, so these differences should not be left unregarded.

Otherwise, the picture for well-posed images is clear, and the choice of color system should be LAB, LHC, HSIp, RGB – in that order. Obviously, this recommendation only takes recognition performance into account, and does not deal with computing performance issues.

Looking at very ill-posed pictures, the choice should be LAB, as some pictures are only managed by that system. LHC performs similarly, but has occasional disadvantages.

It should be noted that (if we leave out very ill-posed pictures), HSIp should be taken into account as an alternative, as it outperforms LAB/LHC in some case when it comes to even performance.

7. FUTURE WORK

As stated above, YUV and HSI performance should not be taken for even to RGB / HSIp. Besides that, there are some aspects that have been deliberately left out of this work, namely dynamic separability (coping with mutual group ambiguities after changes, especially if they are sudden and the predictability of changes). Furthermore, we have not looked at other distance measures, to answer the question if LUV could perform better than LAB if different distance measure were used. All aspects are worth a future look.

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