Soccer Field Detection in Video Images Using Color and Spatial Coherence

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Abstract. We present an original approach based on the joint use of color and spatial coherence to automatically detect the soccer field in video sequences. We assume that the corresponding area is significant enough for that. This assumption is verified when the camera is oriented toward the field and does not focus on a given element of the scene such as a player or the ball. We do not have any assumption on the color of the field. We use this approach to automatically validate the image area in which the relevant scene elements are. This is a part of the SIMULFOOT project whose objective is the 3D reconstruction of the scene (players, referees, ball) and its animation as a support for cognitive studies and strategy analysis.

1 Introduction

The SIMULFOOT project started in Marseilles three years ago within the frame of the IFR Marey, a new organization dedicated to Biomedical Gesture Analysis[1][2]. Our main objective is to provide a technological platform to cognitive scientists so that they can investigate in new theories about group behaviors and individual perceptions, and validate them [3][4][5]. A direct application of this project as suggested by its name is to provide an efficient tool for analyzing soccer games, as it has been described in other similar projects [6][7][8].

There are many problems to solve for implementing this technological platform, such as detecting the players and the ball, or finding landmarks to provide the 2D to 3D registration [9]. But all these elements have to be detected in the field and not out of it (e.g. in the stand): thus, the characterization of the field is the first problem to solve and this is the topic of this paper. Research works have been developed to automatically extract the foreground elements from the background in video sequences, such as those described in [10] and [11]. But the problem mentioned in these papers is quite different although it looks similar: we do not want to characterize the background but to find the area in the image that corresponds to the relevant part of the background. In other words, we want to provide a background segmentation into two parts, the relevant one and the non-relevant one.

Let us also mention the works developed by Vandenbroucke on a method that provide a color space segmentation and classification before using snakes

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to track the players in video sequences [12]. The ideas developed in this paper are very interesting but they do not fully take advantage of the color and spatial coherence, such as the works on the color space described in [13] and [14].

For these reasons, we have developed a new approach that integrates all these features. This approach consists in:

– Analyzing the pixel distribution in the color space
– Characterizing the relevant area in the color space (color coherence)
– Selecting the corresponding points in the image
– Using a spatial coherence criterion on the selected pixels in the image

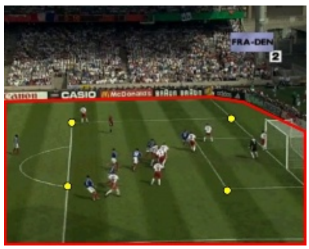


Fig. 1. The selected area is bounded by the red line (points in yellow are landmarks)

We will mainly focus on the color space segmentation that is a very difficult task in many cases. The approach we propose in this paper is robust (on the Fig. 1 we can see there are many variations of green and it works anyway) and it can be applied to a wide set of situations (other than soccer field detection)

The only assumption we make is that the soccer field type of color is majority in the image (i.e. the camera is not oriented toward the stand and does not take a close-up of a player) as illustrated in Fig. 1.

2 Basic Segmentation of the HLS Space

All the pixels of a given image can be represented in a color space that is a 3D space. Usually, the information captured by a video camera is made of (red, green, blue) quantified values. But this color information can be represented in a more significant space such as the HLS (Hue, Lightness, Saturation) one, for example (it provides the expression of the hue that seems determinant in this context).

The first idea we developed was to select points on the basis of a threshold in the natural discrete HLS space. Natural means that we use the set of values associated with the quantified number of (R,G,B) values. The algorithm is very

Table 1. HLS space discret model

Luminance	Saturation	Hue	Cells
[0.95,0.1]	1	1	1
[0.9,0.95]	2	6	12
[0.8,0.9]	4	6	24
[0.7,0.8]	4	12	48
[0.6,0.7]	8	12	96
[0.5,0.6]	8	12	96
[0.4,0.5]	8	12	96
[0.3,0.4]	8	12	96
[0.2,0.3]	4	12	48
[0.1,0.2]	4	6	24
[0.05,0.1]	2	6	12

simple: we count the values occurrences in the HLS space and we keep those with the higher score. It is very simple but it is not efficient at all because of various possible local value distributions. Fig. 2 illustrates this effect: we have selected pixels that occur at least 16 times and we can see that the result is not satisfactory.

Fig. 2. Threshold on points occurrences in the HLS space

These remarks inclined us to use a different approach to analyze the point distribution in the HLS space. We consider this space as a more discrete one (i.e. with a lower granularity level) and we evaluate the contribution of the points (representing the pixels) to each cell (volume element of the discrete HLS space). Then we keep the most significant cells to provide the selection.

3 A Discrete Representation of the HLS Color Space

We represent the HLS space as a set of volume elements each of them being defined by a set of constraints on the H, L and S values. We have chosen the following repartition that provides an interesting discrete model made of 554 cells (each line gives the number of intervals in H, in S and globally for each interval in L).

This discrete representation of the HLS space is illustrated by a set of juxtaposed polyhedrons (Fig. 3) or by a set of small spheres centered in each polyhedron (Fig. 4).

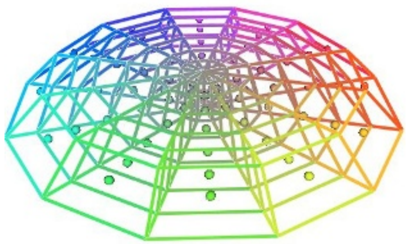


Fig. 3. Polyhedrons representing some of the cells

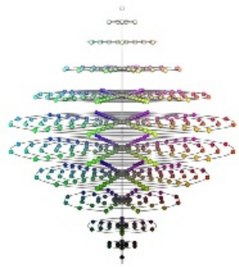


Fig. 4. Complete discrete representation of HLS space

It implies the following neighborhood relations between the cells (Fig. 5 to 9).

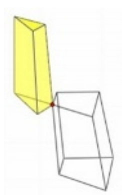


Fig. 5. 8-connectivity (vertices)

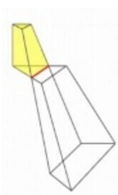


Fig. 6. 12-connectivity (edges)

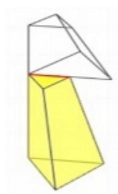


Fig. 7. 24-connectivity (half-edges)

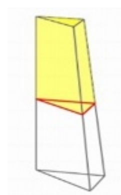


Fig. 8. 6-connectivity (faces)

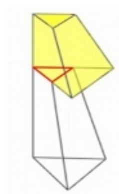


Fig. 9. 12-connectivity (faces)

It improves the initial selection but it still does not provide a full satisfactory result. Fig. 10 and 12 show the decimation process based on a threshold on the cell density and it illustrates an undesired effect: the green cell the most on the right (the most saturated) disappears before the cells along the luminance axis. The effect on the selection is visible on Fig. 11 and 13.

We can notice that only using a threshold on the density is not the best solution. The reason is that in this approach, we do not consider the interactions between cells and consequently, we do not fully take advantage of the coherence in the color space. In order to avoid it, we have decided to induce interactions through cells by considering that each point is a source of potential and by evaluating the generated potential at the center of each cell.

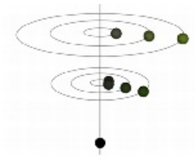


Fig. 10.

Fig. 11.

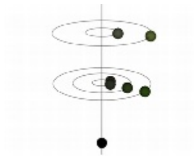


Fig. 12.

Fig. 13.

4 Potential Sources in the Color Space

The potential emitted by each point has a maximum value at this point (the source), it has a zero value beyond a given distance (the range), and it is linear in between. The range is not the same for all the cells because they do not have the same size. Let us consider $R = D \div 2$ where D is the diameter of the cell to which the point belongs (the diameter is the highest distance between two points of the cell). The range of the potential function D_Max is evaluated as $D\_Max = R \times (1 + \varepsilon)$ where *varepsilon* represents the increasing percentage on R and has not to be a small value. Each point contributes to increase the density of a cell if its distance in the center of the area is lower than D_Max. The weaker this distance is, the more the contribution is strong.

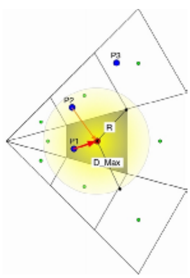


Fig. 14.

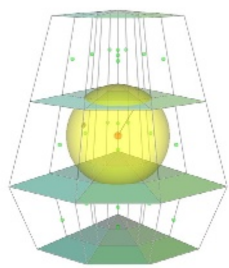


Fig. 15.

Fig. 14 and 15 show the emissions area (in yellow with a variable intensity) in which a given point brings a contribution. For example P1 has a stronger potential value than P2 on the grayed area while P3 has a null potential for this area.

Figures below illustrate how the use potential sources improves the pixel selection through the color space: the cells along axis luminance is eliminated by thresholding before some of the green ones that have a higher value thanks to the contributions of their neighbors (color coherence).

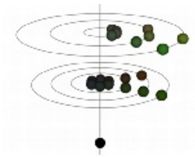


Fig. 16.

Fig. 17.

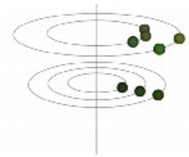


Fig. 18.

Fig. 19.

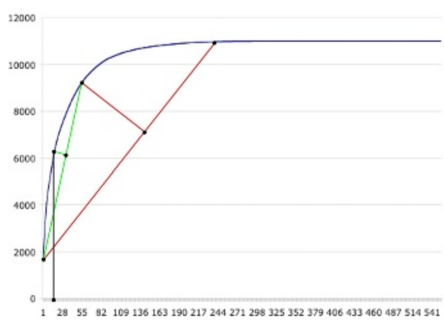
5 Automatic Thresholding and Cell Selection

Up to now, we only considered a manual selection of the threshold value. Let us describe the classical but efficient algorithm we use to automatically select it.

Let us consider the distribution of the potential values in the 554 areas of the discrete HLS space. Most values are low ones and a few of them are high ones. We sort these values by decreasing order and we evaluate the function F that gives their cumulated value (i.e. F(1) is the highest potential, F(2) is the sum of the two highest potentials, and so on).

This function starts at 0, it strongly varies on a few values and then it slowly varies to the value 554 of the variable. The breakpoint of the representative curve is significant of the threshold value. This breakpoint is obtained through the segmentation in two parts of the curve using a split and merge algorithm.

Table 2. Area density cumulated histogram



Once we have automatically determined the threshold value, we start from the area that has the highest density; then, we look for other areas that are connected (neighborhood relations have been defined previously (Fig. 5 to 9)) until we reach the number of areas determined through the analysis of the cumulated histogram (Table 2). The result is a set of areas in the discrete HLS space as represented below (Fig. 20).

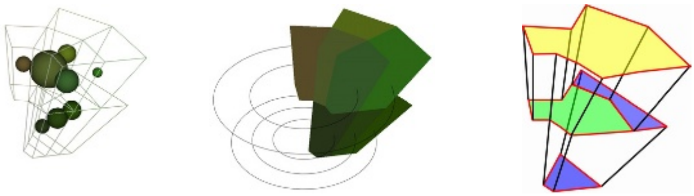


Fig. 20. Set of automatically selected areas in the discrete HLS space

6 Using Area Coherence

We now have to use the area coherence to definitively determine the Region of Interest (the field). There are two kinds of elements on the field: the players (and the ball) and the white lines. The first ones produce holes and the second ones split the Region of Interest into different connected components that are very close one to each other.

First, we apply to this image a closing with a structuring element which size is over the usual line width: it provides the connection between all these connected components. Then, we apply to the result an opening with the slightly bigger structuring element in order to eliminate all the non-significant elements that are close to the border. Finally, we keep the connected component that contains the most pixels and we fill its holes to obtain the region of Interest (Fig. 21).

Fig. 21. The red line outlines the border of the region of interest

7 Conclusion

The approach described in this paper has been developed in the frame of a project in which we can identify a specific background mainly through its color coherence. This approach is quite robust for this application. It could be interesting to develop it in a more general frame (for industrial vision) when various backgrounds are present in the image or when the main component in the color space extends on a wide area.

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