Crossed-Line Segmentation for Low-Level Vision*

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Abstract. This work describes a new segmentation method for robotic soccer applications. The approach called crossed-line segmentation is based on the combination of region classification and a border detector which meet homogeneity criteria of medians. Experiments suggest that the method outperforms traditional procedure in terms of smoothing and segmentation accuracy. Furthermore, existing noise in the images is also observed to be reduced without missing the objects' borders.

Keywords: Color-based Segmentation, Robotic Vision, BLOBs.

1 Motivation

In the context of the RoboCup 4-legged competition, one of the challenging issues has been the dependence of the image segmentation methods on variations of the lighting conditions on the playfield [2]. Despite the fact that official competitions are held in highly controlled lighting, moving people, shadows, etc significantly affect the accuracy of the segmentation methods.

Most of the segmentation strategies [3,1,7] separate the color space by defining areas in which a single color can be identified. However, previous research [2] suggests that a huge amount of color sharing areas in the space depends on lighting conditions.

In this work, a new strategy for color-based segmentation which is a combination of the methods described above is proposed. This uses crossed-line filtering, with a special focus on efficiency issues. Thus we are able to provide effective segmentation at real-time rates. The approach shows several advantages whenever environment conditions do not allow using LUT segmentation properly including its better tolerance to lighting conditions and noise.

This paper is organized as follows: in section 2 the main issues and methods for color-based segmentation in robotic soccer vision system are discussed. Section 3 outlines our new approach to crossed-line segmentation. In section 4, we describe the performance of a system using the method and comparative assessments

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with other representative segmentation methods. Finally, some conclusions and further issues are drawn in section 5.

2 Related Work

Most of the color image segmentation methods require a significant amount of processing which is out of reach on the robots due to demanding speed requirements. For this, these methods use a *Look Up Table* (LUT) that makes reference to a single color value based on the value of one pixel of the target image [4,7]. Accordingly, the number of referenced values becomes less than the total number of colors. One problem with using LUT is that in order to make the processing faster, a big amount of additional memory is required.

Color-based segmentation has been tackled by using decision trees based classification techniques [7]. In particular the $C4.5$ algorithm is applied to separate a multi-dimensional space into different color classes in the YUV space. This uses previously classified pixels so as to isolate and generalize each generated cluster.

Because of these issues, adaptive segmentation techniques have shown to be promising for RoboCup. In particular, *Support Vector Machines* (SVM) have been used to clasify each color class separately. A single class is used to avoid classification errors as each sample to be segmented represents only a part of the space. SVM-based segmentation showed better results than LUT filtering by reducing errors in almost 18%. However, its tolerance to lighting changes has not been proved yet.

Overall, most of these segmentation methods require a set of samples consisting of preclassified colors extracted from representative images on the playfield's conditions. This process does not only take hours but also generates few samples of the candidate pixels obtained from the camera during a game. LUTs used by segmentation methods show huge gaps between points of each color class hence segmentation tries to generalize (i.e., spreed the points' influence) most of the sample set without missing the shape or the relation between each class. The idea here is based on the fact that for points belonging to a color class, the probability that their surrounding points are in the same class is high.

3 A New Crossed-Line Segmentation Method

A new color-based segmentation method is proposed for the 4-legged RoboCup competition. In order to assess its effectiveness, the procedure was compared with two traditional color-based segmentation strategies based on the results obtained from previous RoboCup 4-legged competitions: boundary (limit) segmentation and spatial influence segmentation [4].

Our proposed method, called *Crossed-line Segmentation* is based on region segmentation but uses a median-based homogeneity criterion and a color-difference border detector. The method works under the assumption that average points tend to be more stable than separated points providing that images are very noisy in spaces where regions of the same color can be identified.

In order to reduce noise, the method scans an image at one direction from one side to the other by assigning the average value of the same color to each point. The procedure stops whenever significant changes on the line are found. The crossed-line segmentation is so described as follows:

ALGORITHM Crossed-Line Segmentation
INPUT: image with features width (n), margin (m), median (X_c)
points of one line of the image $\{x_1, x_2, ..., x_{n-1}, x_n\}$
current position (i), starting point of the sequence (i_0)

Segmentation starts at position $i = 1$
(1) $X_c = x_i$, $\sum c = x_i$, $i_0 = i$
(2) IF $i \leq n$ THEN
$i = i + 1$
GOTO (3)
ELSE GOTO (4)
(3) IF $|X_c - x_i| > m$ or (i is a border point) THEN
$\forall x \in \{x_{i_0}, ..., x_i\}, x = X_c$
GOTO (1)
ELSE $\sum c = \sum x_{i_0}, ..., x_i$, $X_c = \sum c : (i - i_0)$
GOTO (2)
(4) FOR ALL x $\in \{x_{i_0}, ..., x_i\}, x = X_c$
Advance one line
GOTO (1)
END

The margin (m) is experimentally defined and the border (step (3)) is detected by using the border detector operator. Although the procedure works for one channel, this can also be applied to three YUV channels by computing the sums and averages for each channel. Whenever the absolute value of the difference between the median and the point exceeds the margin for the three channels, the median value is assigned to the predecessors of each channel. Once the image is segmented, compression is carried out by using RLE.

Applying this method has a smoothing effect on every point not meeting the separation rule. The procedure also complies with the region segmentation conditions [6] in which every point belongs to a surrounding region only if $|X_c - x_i| > m$ and this is not at the image's border.

The problem with using one direction (either horizontal or vertical) is that the average for one direction may be different from that for the orthogonal direction, though the color-based segmented with this average is likely to be the same. To deal with this issue, the strategy is applied twice at different directions and the result of each scan is stored into a temporary image containing the averages (figure 1). Furthermore, the algorithm's behavior is the same for the three cases. Results of the segmented image can be seen in figure 1. In order to define the margin m, different testings were performed by filtering three representative images. These represent the ball at one of the corners, a landmark and the ball

Fig. 1. Different applications of *Crossed-line Segmentation*: left to right, and downwards

in front of one arch. For every image, the margin's value is increased and the number, width and height of the BLOBs (*Binary Large Object*) representing the amount of noise is recorded.

Results of these experimental settings suggest that the method gets stabilized between margin values 20 and 70. For values above 70, width and height values get unstable. The margin should be kept big enough to reduce the noise and small enough to avoid removing small areas of interest, hence the margin used for our competition has been set to 25.

The influence of the border filter on the crossed-line segmentation was also assessed. For this, the previous three images were used again and the parameters used to set the margin were kept.

The method with and without border detection shows similar stable behaviors for the same margin settings (20-70). All the graphics show that width and height values are almost the same for the range 20 to 70. Both criteria become unstable whenever the margin exceeds 70. However, using borders shows better and stable behavior for values above 70, whenever the detection quit providing information on the differences of medians. For the remaining experiments, the method using the border detector was evaluated as this satisfies the region segmentation rules [6]. It is important to highlight that time efficiency was not an issue as the time spent by this operator is not significant for the current testings.

4 Comparative Experiments

In order to evaluate our crossed-line segmentation method and compare it with other segmentation methods, several experiments were carried out under different lighting conditions: fixed and variable. The aim was to assess metrics such as segmentation accuracy, noise and light tolerance, etc. Each method analized 41 images, scenarios and locations in which each SONY AIBO Robot gets involved during playing time. In addition, segmentation for 17 images using variable lighting, different from the previous set of images, was also considered.

Each segmented image was characterized based on numeric information obtained from the BLOBs representing color areas of interest. The target data included the number of BLOBs for every image, the number of BLOBs of a specific color, average width and height of the generated BLOBs, and the width and height of the biggest BLOB in the image. To assess the existing methods under ideal conditions, a list of manually defined BLOBs was defined. Next, crossed-line segmentation was compared with the median-filter segmentation by applying a $5x5$ filter on the points of the image. This was then segmented using the LUT technique. Because of the method's image smoothing by using average values of a set of pixels, the results were roughly similar to the median filter.

In order to compare the proposed strategy with traditional median filters, a configuration setting was used by applying a $5x5$ media filter on the image's points and then had it segmented via LUT. For the experiments, a set of images extracted from several localizations on the playfield was obtained [7] with different features.

Results of applying different segmentation methods for under fixed lighting can be seen in figure 2. Both LUT and boundary segmentation generate big amounts of noise, and a huge number of average BLOBs above 200 for each image with a average size of $5x5$. Median filtering and LUT segmentation produced almost no noise because the image has been slightly smoothed above the median filter's value.

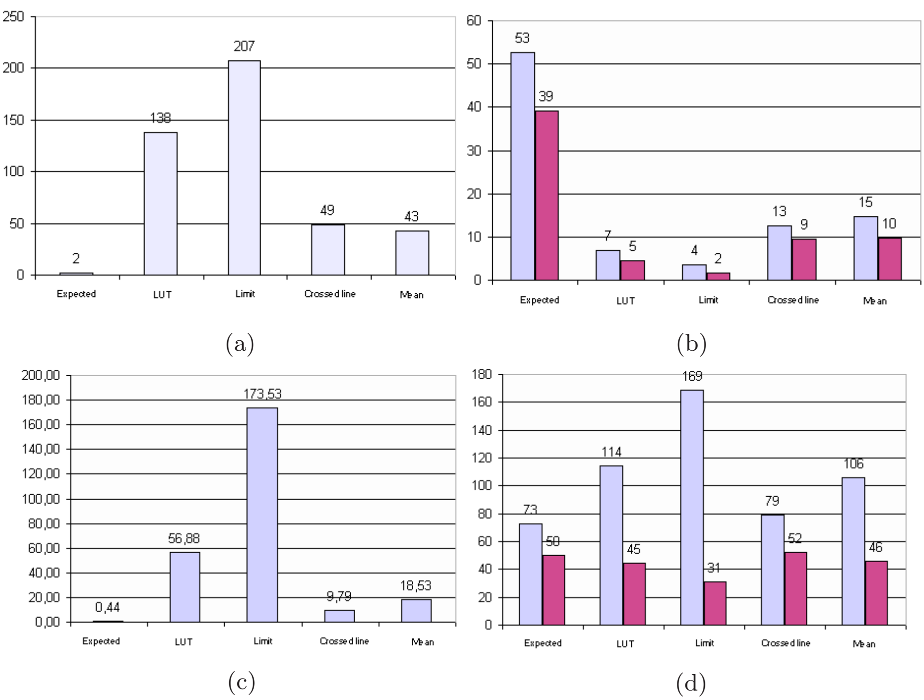

Fig. 2. Segmentation using fixed lighting: Average number of BLOBs per image (a), Average Width and Height of the BLOBs in pixels (b), Average Radius of BLOBs (c) and Average height of the Biggest BLOB (d)

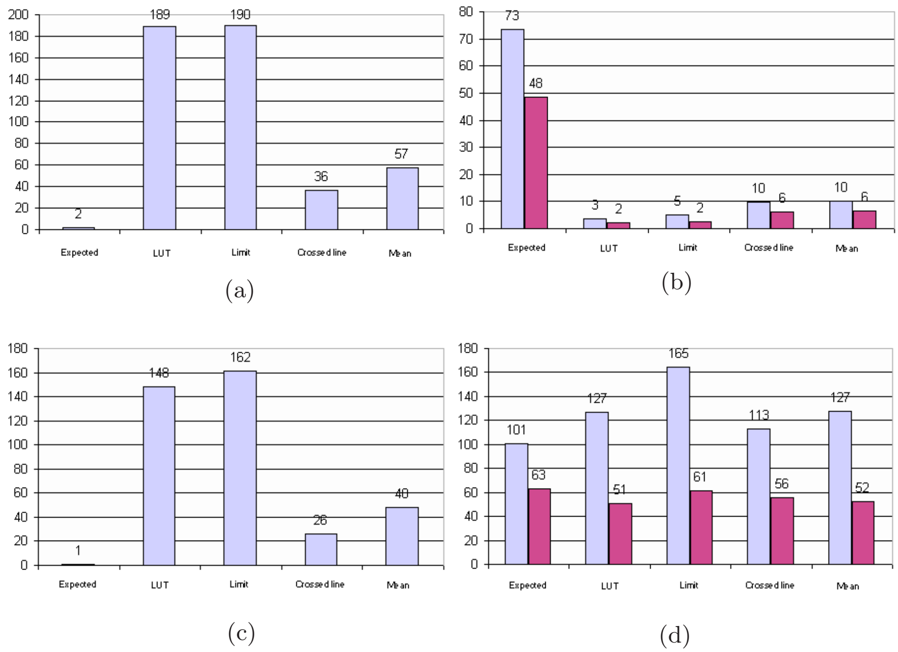

Fig. 3. Segmentation using variable lighting: Average number of BLOBs per image (a), Average Width and Height of the BLOBs in pixels (b), Average Radius of BLOBs (c) and Average height of the Biggest BLOB (d)

Crossed-line segmentation shows a similar behavior on noise reduction having 1/3 less of BLOBs than LUT segmentation alone. Both methods have the same average size of BLOBs, bigger than LUT and limit segmentation, which is due to the existing noise reduction: median filtering tends to concentrate big amounts of noise and transform this into *solid* areas by joining noise points which were previously separated.

Colorimetric distortion affected all the tested methods being the limit segmentation that having the worse performance. Figure 2(c) shows a median close to 174 blue BLOBs per image even when the ideal amount is less than one. This effect can also be observed for generalized LUT segmentation. Graphics in figure 2(c) also shows that settings for the median filter and the crossed-line segmentation have a smaller media value for blue BLOBs as small noise areas are concentrated into bigger regions and so low-intensity noise is removed by the filter. In addition, bigger decreases in line segmentation may be due to the fact that most of the classified points (i.e., blue for LUT segmentation) have been classified using colors not included in the table (i.e., black areas).

As for the height and width of the biggest BLOBs, line segmentation proved to get values closer to the ideal, whereas for limit segmentation, because of bigger areas of blue, the method produced width values that are far from the ideal sizes.

Variation in size can also be explained in terms of colorimetric distortion of blue which increases the BLOBs size.

Sampling using variable lighting showed a behavior similar to the previous case despite the fact that the quality of segmentation for each method decreased significantly. One explanation for this is the big changes of lighting conditions produced by the influence of sunlight on all the areas of the playfield.

A significant increase in the number of BLOBs for both limit and LUT segmentation (almost 200 BLOBs per image) can be seen at figure 3(a). Colorimetric distortion had an impact on the increase of the quality of BLOBs as seen at figure 3(c). However, some areas of the playfield are identified with incorrect colors caused by sunlight which, in turn, allows the green playfield area to be classified using white, blue and yellow colors. It is also important to stress that the average size of the biggest BLOBs for linear segmentation gets closer to the ideal size as for the previous samples. Unlike the median filter which smooths the border making their definition difficult by modifying their size, our approach generates an accurate segmentation for the border of the objects in the image.

5 Conclusions

A new method for image segmentation using a crossed-line filtering strategy was proposed. The approach shows several advantages whenever environment conditions do not allow using LUT segmentation properly. Under noisy images segmented via LUT, the method smooths most of the noise, specially in bigger areas of the same color. Other promising feature is its ability to remove noise from images with no loss of quality of the objects' borders.

This advantage is specially useful for RoboCup because for images very distant from arches and landmarks, a difference of 2 or 4 pixels may produce several centimeters of error in localizing objects. Unlike traditional smoothing techniques, our method does not only avoid border blurring problems but this stresses them. This is a key issue in RoboCup as for images very distant from arches and landmarks, a difference between 2 and 4 pixels may imply several centimeters of error to localize the objects. One of the drawbacks is that the strategy tends to erroneously classify smaller color areas or those with slight changes from one color to other as points show differences between colors that are lower than the selected margin. The procedure to analyze a full image runs on linear time and is very similar to spatial methods such as median filters. In addition, although all the segmentation methods are affected by colorimetric distortion, the crossed-line proved to be less subject to these variations.

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