Real-Time Adaptive Colour Segmentation for the RoboCup Middle Size League

Claudia Gönner, Martin Rous and Karl-Friedrich Kraiss

Chair of Technical Computer Science
Technical University of Aachen (RWTH)
Ahornstr. 55, 52074 Aachen
{Goenner,Rous,Kraiss}@techinfo.rwth-aachen.de
`www.techinfo.rwth-aachen.de`

Abstract. In order to detect objects using colour information, the mapping from points in colour space to the most likely object must be known. This work proposes an adaptive colour calibration based on the Bayes Theorem and chrominance histograms. Furthermore the object's shape is considered resulting in a more robust classification. A randomised hough transform is employed for the ball. The lines of the goals and flagposts are extracted by an orthogonal regression. Shape detection corrects over- and undersegmentations of the colour segmentation, thus enabling an update of the chrominance histograms. The entire algorithm, including a segmentation and a recalibration step, is robust enough to be used during a RoboCup game and runs in real-time.

1 Introduction

A scenario for teams of mobile robots, in which optical sensors are very important, is RoboCup. In the middle size league this was forced by an environment, where objects like the orange ball can primarily be detected by optical sensors. The field is adapting towards the FIFA-rules step by step. The most important rule change in this category was the removal of the board. Illumination was decreased and variable lightening conditions, e.g. playing under sunlight, are subject of discussion.

At the moment RoboCup is ideal for applying colour segmentation algorithms. All objects have characteristic colours, e.g. the yellow and blue goals, permitting a classification in the colour space. To achieve frame rates between 10 and 30 Hz a fast scene segmentation is necessary. The main issue with colour segmentation, though, is calibrating the object colours.

Well known real-time colour segmentation methods are the definition of colour regions by thresholds [1–3], colour clustering [4], occupancy grids [5] and discrete probability maps [6]. Thresholds are either manually set [1] or trained by decision trees [2] and neural networks [3]. Probability maps may be approximated by Gaussian mixture-models [7] to save storage place.

To distinguish different colours by thresholds in an efficient manner, specialised colour spaces have been adapted to particular object colours [8]. In contrast to these threshold-based algorithms, probability maps make no assumptions about the outline of object colours. The number of colour regions does not need to be provided a priori as with k-means clustering or Gaussian mixture-models. Furthermore probability maps separate different objects based on the Bayes Theorem in a statistically sound manner and also consider the background. The occupancy grids of [5] are similar to probability maps, but do not model the background, use increment and decrement operations on the grids and accumulate a term considering the landmark confidence and area. Probability maps, however, distinguish a priori and object probabilities while computing the a posteriori probability.

In addition to colour information, the object shape may be utilised for object classification. Jonker, Caarls et al. [9] verify a ball hypothesis by two hough transforms, executed successively. Hanek, Schmitt et al. [10, 11] fit a deformable contour model to edges and propose an image processing that is independent of colour segmentation. Depending on the parametrisation of the contour model different shapes are detected. Their approach requires a rough initialisation of the adaptive contour model.

This work introduces a method to generate the mapping between single objects and their chrominance automatically. It is based on histograms which are combined according to the Bayes Theorem. Colour segmentation is combined with a shape detection to provide additional robustness and allow colour recalibration. The shape detection specialises on RoboCup and recognises the ball, the flagposts and the goals with their white posts. Whereas the adaptive colour segmentation is generally applicable, as long as a second segmentation is provided for the colour update. A prior version of the presented algorithm was published in [12], suggesting a supervised colour calibration.

2 Overview

Colour spaces that distinguish between luminance and chrominance are well suited for colour segmentation. Bright and dark objects of the same chrominance may be distinguished by their luminance. This work is based on the YUV space, which is supported by most video cameras and therefore does not require any conversion.

In order to compute the chrominance histograms of each object, an object detection is required that either does not utilise colour information or extrapolates incomplete results of a colour segmentation. The latter approach has been chosen here, sketched in Fig. 1. Image regions occupied by the objects of interest are marked using an initial table, which contains the mapping between the chrominance and the classified objects and is referred to as colour map. This map (Fig. 2) can be drawn by hand or recycled from a former tournament.

After applying the colour map, the object's contour and neighbourhood relations are checked to verify whether it really is a ball, a goal or a flagpost. On success histograms of the object colours are updated and a new colour map is calculated. To save computation time the histograms only need to be adjusted on change of the lighting conditions, i.e. the colour segmented area and the

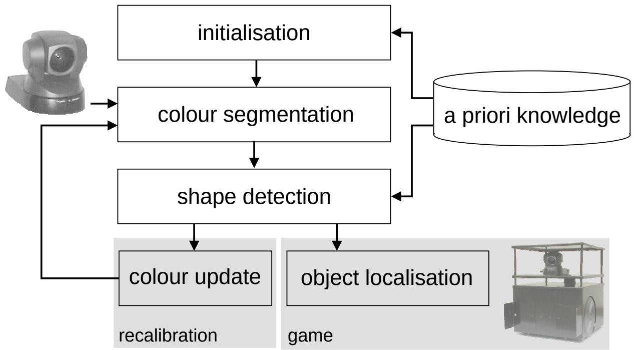

Fig. 1. Outline of the adaptive colour segmentation.

shape detected silhouette differ. Furthermore the colour map is recomputed after a fixed number of histogram updates. Colours that did not occur for a while are eliminated because the histograms are rescaled from time to time. To avoid complete deletion the histograms are scaled only if they contain more than a minimum number of entries.

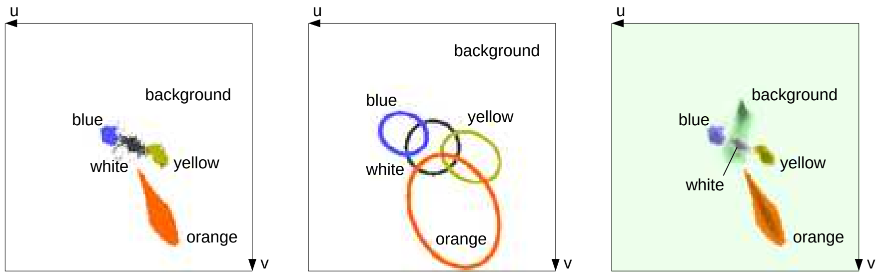

Fig. 2. *Left:* Colour map. *Middle:* Chrominance sets. *Right:* A posteriori probabilities.

Because of the iterative nature of the entire process a second map is added that specifies the maximum chrominance set (Fig. 2) for each object, including the background. In contrary to the colour map, these sets may overlap. They prevent divergence of the algorithm without loss of generality. Currently the maximum chrominance sets are provided a priori and kept static during a game.

3 Colour Training and Segmentation

Prior to colour segmenting an image, the chrominance histogram H_O for each object O in the object set $\mathcal{O}$ is computed. In this context, the background is also considered an element of $\mathcal{O}$. The relative frequencies in the histograms H_O can be interpreted as the a priori probabilities $P(u, v|O) = H_O(u, v)/|H_O|$ for occurrence of an (u, v)-pair under the assumption that object O is seen. The a posteriori probability, specifying how likely an (u, v)-pair belongs to object O, is given by the Bayes Theorem:

$$P(O|u,v) = \frac{P(u,v|O) * P(O)}{\sum\limits_{Q \in \mathcal{O}} P(u,v|Q) * P(Q)}. \tag{1}$$

McKenna, Raja et al. [7] note that the object probability $P(O)$ is related to the object size. However it is rather difficult to record images containing the objects in representative quantities. Therefore $P(O)$ is not computed, but set manually.

If a chrominance pair (u, v) has not been seen yet on object O an initial probability $P_{init}(u, v, O) = P_{init}(u, v|O) * P(O)$ is assumed, preventing that a chrominance pair gets a high a posteriori probability although it is barely contained in object O.

At each pixel the object with the highest a posteriori probability is classified. For an efficient classification the object belonging to a chrominance pair is stored in a look-up table, i.e. the colour map as visualised in Fig. 2. The figure also shows the probabilities of the classified objects, where darker values correspond to higher probabilities. In the centre, representing the achromatic area, white posts in the foreground overlap with white, black or grey background. The green floor is considered as background.

As long as the lighting condition remains constant the same colour map is applied and the complexity is identical with [13, 9]. On a lighting change the histograms and the colour map are updated. In order to eliminate old entries the histograms are scaled by a time-out factor prior to adding new images.

4 Ball Detection

Colour segmentation identifies image regions, which might contain interesting objects. Due to occlusions or bad segmentations, especially while the colour map is adapting, the object's segmentation might not be complete. Figure 3 shows a typical segmentation performed with an initial colour map. The upper half of the ball is not completely segmented. However, there is enough information to extrapolate a circle with the colour segmented contour points.

To detect partially occluded objects of known geometry we apply a randomised hough transform. Although the projection of a sphere on a plane results into an ellipse [11], we model the ball as a circle. This approximation is sufficient for verification and completion of the ball's shape.

A circle has three degrees of freedom: the centre (c_x, c_y) and the radius r, resulting in a 3D hough accumulator. If only a few round objects are inside the region of interest the search space is reduced with a random approach. The implemented randomised hough transform is based on the work of McLaughlin [14] and Xu, Oja et al. [15].

First, three points (x_i, y_i) on the contour are randomly selected. Considering the triangle, which is formed by these points, its centre of gravity coincides with

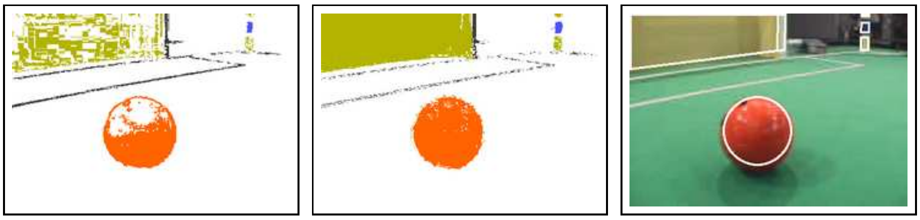

Fig. 3. *Left:* Initial colour segmentation. *Middle:* After recalibration. *Right:* Original image, in which the detected ball, flagpost and goal are surrounded by white lines.

the circle's centre and all distances from the centre to these points have about the same length if the points lie on a true circle. If this test is passed the hypothised centre $(\hat{c}_x, \hat{c}_y)$ and its average distance $\hat{r}$ to all triples are inserted into the hough accumulator. It is advisable to store the occupied accumulator cells only because just a few cells are filled [14].

After the specified number of point triples has been drawn and added to the accumulator, the cells with the highest counts are verified. The best hypothesis is determined by the weighted sum of the ratio e_p between the circumference and the perimeter of the approximating polygon, the signal to noise ratio e_{SN}, and a radial error e_r. All measures are normalised to values between 0 and 1. Thereby the error e_r of the radius is modelled as Gaussian and a probability for the hypothised radius $P(\hat{r})$ is calculated from the mean μ_r and variance σ_r^2 of all point distances to the centre $(\hat{c}_x, \hat{c}_y)$:

$$e_r = P(\hat{r}) = \frac{1}{\sqrt{2\pi}\sigma_r} e^{\frac{(\hat{r}-\mu_r)^2}{2\sigma_r^2}} \tag{2}$$

A hypothesis is valid if each measure is above a fixed threshold. If no circle is detected the procedure may be repeated. Partially occluded balls occasionally require such a repetition. Due to the randomised approach and noisy data it is recommended to verify more than one hypothesis at each cycle.

5 Detection of the Goal and Flagposts

Contrary to the ball, the shape of the goal and flagposts cannot be concluded from the colour segmented contour if a bad colour map is applied (Fig. 3). If so, the colour segmented area is ragged. Therefore object detection uses edges close to the colour regions. Also neighbourhood relations are considered. Sideways to a goal a white bar is expected. Due to partial occlusions a single collateral white region is sufficient. The flagposts are characterised by vertical yellow-blue or blue-yellow transitions.

As the robot's camera looks downward, the upper borders of the goal and flagposts are never visible. Thus only straight lines bordering the side and the bottom are checked. Lateral to the goal the inner and outer line of the white bar are determined. This allows construction of a histogram for white regions.

The lower line of the flagpost is approximated by a horizontal line. All other lines are extracted by orthogonal regression [16] applied in a recursive manner. Thereby the point set is split along the regression line until the desired precision is reached or too few points are left. The line with the smallest distance to the colour segmented contour is chosen if more than one straight line fits.

6 Results and Discussion

At the moment colour recalibration supports the ball, the goals including the white posts and the flagposts. All other objects are modelled as background. By considering the objects' shape oversegmentations and undersegmentations are corrected. This enables learning new colours and updating the colour map. Figure 3 compares application of the initial and the calibrated colour map.

Due to the statistical approach, the system is able to distinguish between objects of similar colours, e.g. the ball and human skin (Fig. 4). If the colours of different objects overlap the probability $P(O)$ controls which object is preferred. As no restrictions are placed on the form of the clusters in colour space, an object may contain several non-connected clusters. Clusters belonging to different objects may interlock.

The invariance of the YUV colour space against changes in brightness and lighting is limited. Furthermore the colour map only contains values that have been seen before. Thus a recalibration is required upon new lighting conditions. Both, Fig. 4 and 5 start with a segmentation based on the colour map trained for Fig. 3, but have been recorded in an office environment. In Fig. 4 the colour map

Fig. 4. *Left:* Colour segmentation of a ball, a bare foot and red posts. *Middle:* Circle detected in the left image. *Right:* Colour segmentation after training.

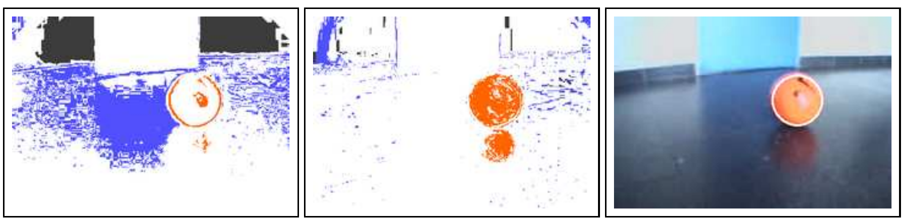

Fig. 5. *Left:* Colour segmented ball after sudden occurrence of sunlight. *Middle:* Colour segmentation after recalibration. *Right:* Detected ball after recalibration.

specialises on the ball and discriminates skin and other red background objects. Figure 5 shows a ball under sunlight, which is recognised as an orange ball merely at the border regions, but still has a circular contour. After recalibration the entire ball is colour segmented again.

The system distinguishes between variably round objects and chooses the best. In Fig. 5 the ball is detected despite of its circular mirror on the floor. Partially occluded balls are extrapolated by the randomised hough transformation, see Fig. 6.

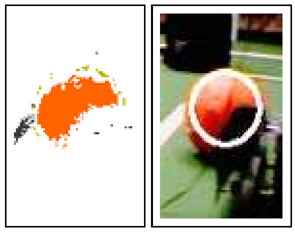

Fig. 6. *Left:* Segmentation. *Right:* Extrapolated circle.

In general the detected circle is smaller than the true ball. This is caused by shadows, inter object reflections and a surface that is not lambertian. Depending on the lighting condition the ball's bottom is very dark and overlaps with achromatic colors (Fig. 6). The ball's boundary is similar to yellow. Furthermore the ball's colours compete with skin and other background objects.

The circle's centre and radius tend to vary a bit from iteration to iteration. This is caused by randomly selecting point triples and a contour which is not perfectly circular. Increasing the number of samples, which are drawn when building the hough accumulator, results in marginal improvements. All circles in this paper are detected based on 25 samples.

The goal and the flagposts are modelled as quadrilaterals, whose lines are detected separately from another. Depending on the quality of edge detection and colour segmentation lines may be chosen that lie close by or on the objects, but not at the true border. The presented approach does not distinguish between the two lower lines of a goal looked at from the side.

However, too big goals and flagposts are critical merely at the beginning of the training process. Marking incorrect objects in an image influences the colour map if and only if the a posteriori probabilities of all other objects including the background are lower. These a posteriori probabilities primarily depend on the relative frequency in the histograms. As long as the histograms contain few entries, wrong entries result in higher frequencies as later on, when the correct maxima have many hits. Thus colour calibration is quite sensible to oversegmentations at the beginning. After some images have been trained, wrong segmentations have minimal effects. Old erroneous entries are decreased by the time-out factor and finally erased. To avoid divergence only potential object colours are filled into the histograms as specified a priori by the maximum chrominance sets.

The entire algorithm is implemented in C++ using the computer vision library LTI-Lib [17]. As runtime varies due to image content, 163 RoboCup images of 379×262 pixels are analysed on a Pentium III processor with 933 MHz, which is build into our robot. Both, the histograms and the colour map, are updated at each cycle. During a game recalibration only needs to be executed on lighting change. Object detection requires at least 24.28 msec, at most 55.68 msec and on the average 33.84 msec. Recalibration takes from 51.23 to 79.40 msec and averaged 59.23 msec, when the chrominance histograms and colour map are computed with 64 entries in each dimension. In our experiments we did not notice a quality difference between colour maps with 64×64, 128×128 and 256×256 entries.

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