CERTAINTY COLOR MAPS COMPARED TO HISTOGRAMS

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ABSTRACT

We present a new segmentation algorithm based on probabilistic histograms and introduce certainty calculus and certainty color maps to solve the difficult problem of histogram separation. This new method is then compared to simple histogram and normalized histogram techniques. Using a set of experiments designed to measure the quality of segmentation, we have shown that certainty color maps is a much more accurate approach than histograms, especially when histogram separation in necessary.

1. INTRODUCTION

Region-based segmentation algorithms ([1, 2]) try to divide the image into homogenous regions, according to a given property like color or texture. When these segmentation methods are used as part of a more general tracking algorithm working on video sequences, the difficult problem of region matching from frame to frame arises. This implies identifying two regions in successive frames as being identical or belonging to the same object (see [3]). However, region matching raises problems including, among others, fast moving object tracking, object persistance through time, object occlusion or objects composed of more than one region.

The option chosen here is to avoid the problem of region matching by using a property of the objects, namely color, to identify and consequently locate and track objects. This approach is not new. Histograms are usually used for this purpose ([4]) and the results are reasonably robust despite light change, object shape change or orientation.

However, histograms or normalized histograms present several limitations that are detailed in this article. To overcome these limitations, we propose a new color representation, called certainty color maps, based on the notion of probabilistic histograms. We outline briefly here the principles of certainty color maps and probabilistic histograms (see [5] for more details and experiment results) and then compare this new method to standard histogram technics and show experimentally that certainty color maps lead to a significant segmentation accuracy and quality improvement.

2. CERTAINTY COLOR MAPS

Active zone: in the following, we assume that the system has memorized a snapshot of the background and that it only considers the pixels of the image that differ from the recorded background. This defines what we call the *active zone*. When we refer to histograms or more generally to color maps, they will be taken implicitly over this active zone only.

2.1. Limitations of histograms and normalized histograms

We call "color map" any representation of the colors present in the active zone. Histograms are one kind of color map. There are two desirable properties that should meet any object color map:

- Invariance with respect to the size of the object in the image (size of the *active zone*)
- Possibility to perform simple operations like substraction

The second property is important when two objects are present in the active zone and we want to separate their respective contribution to the color map.

If we consider simple histograms that record the number of pixels of each color in the active zone, we can satisfy the second property. Numbers can be substracted and the result is still a histogram. But these color maps are not invariant with respect to the size of objects. One solution is to use normalized histograms that give the proportion of each color in the active zone. In that case, the first property is satisfied but not the second. It is not possible to substract proportions unless we first de-normalize the representation, which is not always possible. De-normalization requires the size of the objects in the active zone. When there is only one object, this size can be well approximated by the size of the active zone. When there is more than one object, we need to perform a pre-segmentation of the active zone using a classicial segmentation algorithm, which can fail.

To satisfy both the first and the second property, we have defined to notion of probabilistic histograms.

2.2. Probabilistic histograms

We started from a simple observation concerning normalized histograms. They contain information on the proportion of pixels of any given color in the active zone. If this proportion is non-zero, we know that the color is present and at the same time, we know what *amount* of this color is present. Both informations are relevant and useful for object recognition where proportion can help to distinguish between two similarly colored objects. However, information on proportion is not relevant for object tracking. Here is a simple example to illustrate this point: let us assume we have learned two objects A and B both containing red color but in different proportions. Let us say for example that A has twice as much red than B. In a very classical way, the system scans the active zone and tries to attribute an object label (A or B) to each pixel, according to the color. If it uses the proportion information it will attribute each red pixel to object A because there is more red in A than in B. This is obviously not always a good guess. The only reasonable answer the system can give for the red pixel is *"unknown"*. Then, another algorithm can try to resolve the ambiguity by using the spatial or temporal context of this pixel, but this can not be decided on the base of proportion only.

The notion of probabilistic histograms that we have developed does not use proportion information. We start from a classical normalized histogram of the active zone. Then, a given color will be stated as "present" if its proportion exceeds a threshold, $minprop$. It is then assigned the value 1. Otherwise, it is considered as noise and is given the value 0. The probabilistic histogram is the result of averaging this thresholding over several images (note that it is only possible with video sequences). For a given color C, we write μ_c its proportion in the normalized histogram. The probabilistic histogram p_c is approximating:

$$p_c = proba(\mu_c > minprop)$$

The probabilistic histogram is a kind of color map and it satisfies both the first property because it is based on a normalized histogram and the second property because probability can be manipulated in a well defined mathematical way. In particular, it is possible to perform a kind of substraction operation between two probabilistic histograms. The result of this substraction operation is what we call a "certainty map".

2.3. Histogram separation: certainty color maps

2.3.1. Description of the problem

Suppose we want to learn the probabilistic histogram for object A and object B. The simpliest way of doing it is to show object A and memorize the probabilistic histogram of the active zone and to do the same for object B. The problem arises when object A is the users hand and we want to use the hand to show object B which is, let us say, a red ball. In that case, we have a probabilistic histogram P_A for object A and another one, P_{AB} for object A and object B in the same image. Using these data, we would like to derive a description of the colors specific to object B.

2.3.2. Certainty calculus

Certainty is a measure of how sure we are that a given color belongs to an object. For example, if we measure that $p_A \simeq 1$, we would probably have $p_{AB} \simeq 1$ and in that case we are not at all certain whether the color belongs to object B or not. So the corresponding measure of certainty c_B should be near zero. To be more precise concerning the notation, the certainty measure is calculated by *opposing* object B to a previously known object A, so it should be written as $c_{B/A}$.

In the following, we will consider one specific color C, the reasoning can be extended to any color of the histograms. We define the certainty for object B *opposed* to object A as the probability that the color C is in the joint histogram of A and B without being in the histogram of A. This is an exclusive notion since the colors of A are "excluding" the corresponding colors of B.

By extension, the certainty for object A is simply the probability of C being in the histogram of A:

$$\begin{cases} c_A &= p_A \\ c_{B/A} &= p_{AB} \cdot (1 - p_A) \end{cases}$$

This certainty measure defines a new kind of color map called "certainty color maps". In simple cases, it is equivalent to a probabilistic histogram. In more complicated cases, when it is necessary to perform a histogram separation and the color map can be obtained only by substracting color maps, the result is a measure of the certainty, in an exclusive way that prevent overlapping in the color space.

3. COMPARISON BETWEEN CERTAINTY COLOR MAPS AND HISTOGRAMS

If certainty color maps are interesting from a theoretical point of view, it is still very important to compare this technique to other approaches in order to conclude on its validity. We have designed a set of experiments to measure the quality of the segmentation with certainty color maps compared to simple histograms and to normalized histograms.

3.1. Experimental protocol

We present to the camera the hand of the experimentator and four kind of objects with different colors (each object is represented by a number between 1 and 4). First, there

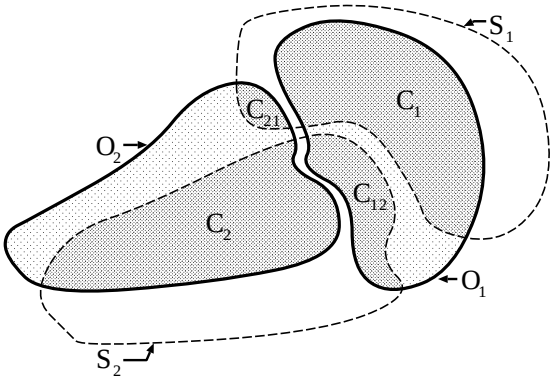

Fig. 1. Regions involved in the score computation

is a training phase where the system has to learn the color maps for each object and for the hand. The hand is learned first, with no other object in the image. In that case, for certainty color maps, the system is learning a simple probabilistic histogram. For histograms or normalized histogram, the system learn an averaged color map.

The second step of the learning phase is the learning of the objects. In that case, both the hand and the learned object are present in the image and the system has to separate their respective color contributions in the color map. With certainty color maps, it uses the certainty calculus as we described it in 2.3.2 (it is *opposin* the object to the hand). With histograms or normalized histograms, the operation used is a substraction.

Then, for the testing phase, we use images where both the hand and the object are present. Five such images are used for each object, with different lighting conditions and hand/object positions. The result of the different methods is compared to images presegmented by hand, and a score between 0 and 1 is calculated, so we can compare them.

3.2. Score calculation

One important requirement for this study is to be able to evaluate the quality of the segmentation. For a given image including two objects, we have defined by hand two regions O_1 and O_2 where the objects are really located and the algorithm is providing us with two candidate regions S_1 and S_2 where the objects are supposed to be located, according to our method. In an ideal situation, we should have $O_1 = S_1$ and $O_2 = S_2$. To measure the distance from this ideal case, we introduce the following quantities for objects i and j (see figure 1):

$$\begin{aligned} C_i &= O_i \cap S_i \\ C_{ij} &= O_i \cap S_j \end{aligned}$$

Then, we calculate the score by taking the min of the following quantities (we consider the cardinal of the regions, written here with a bar on the top):

$$\frac{\overline{C_1}}{\overline{O_1}}, \frac{\overline{C_1}}{\overline{S_1}}, \frac{\overline{C_2}}{\overline{O_2}}, \frac{\overline{C_2}}{\overline{S_2}}, 1 - \frac{\overline{C_{12}}}{\overline{O_1}}, 1 - \frac{\overline{C_{21}}}{\overline{O_2}}$$

When there are several images available, the score is calculated in the worst case by taking the min of the score of each image.

3.3. Construction of S_1 and S_2

The segmentation algorithm used is very simple: for each pixel in the image, with color c, the previously learned color maps (certainty color map, histogram or normalized histogram) are compared to see which object has the highest value for c. In the case of certainty color maps, this value must be above a minimal threshold for the pixel to be attributed to the corresponding object (otherwise it is labelled as "unknown"). This threshold and other internal parameters have been set to optimal values, according to results from a parameter space exploration we have described in [6].

3.4. Results

The following graphics (figures 2,3,4,5) show the comparison results for the four objects we have tested. On the left, there is a group of three bars indicating the scores for the certainty method, the simple histogram method and the normalized histogram method. On the right, there are six groups of bars for the six ratios used in the score calculation. Region 1 stands for the object and region 2 for the hand.

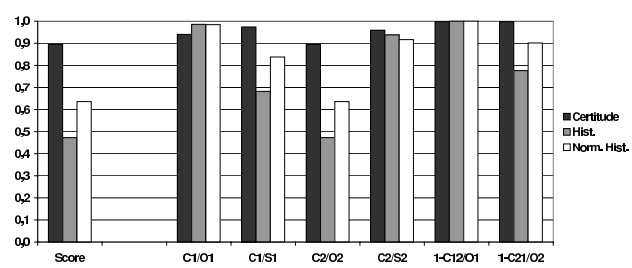

Fig. 2. Comparison results for the red object

The certainty calculus is much more efficient than the two other methods. Normalized histograms get better results that simple histograms, mainly because the objects' distance to camera is different for each testing image and learning set, leading to different object sizes in the images (this has been carefuly checked to ensure realistic experimental conditions). Only the normalized histograms and certainty color maps can deal with varying size. The poor

results of normalized histograms is due to the ill-defined substraction operation, without prior denormalization. Basically, if we look at the resulting segmentation, we can see that parts of object 1 are seen inside objet 2.

These results prove the interest and validity of the certainty color maps over a simple method based on histograms, especially when it is necessary to do histogram separation to learn the color map of the objects.

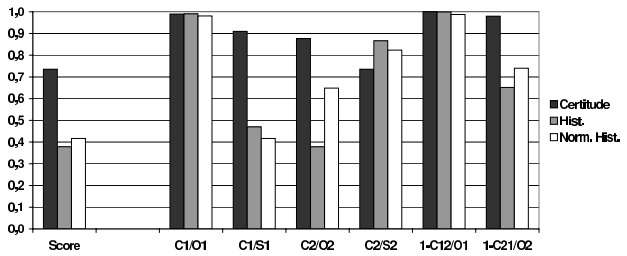

Fig. 3. Comparison results for the yellow object

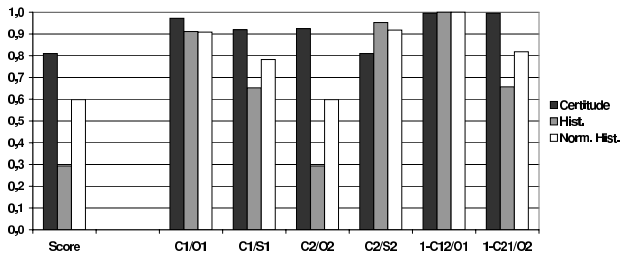

Fig. 4. Comparison results for the green object

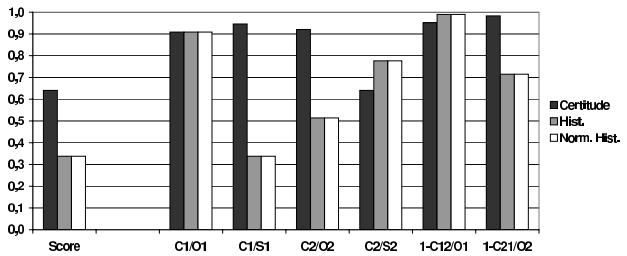

Fig. 5. Comparison results for the white/blue object

4. CONCLUSION

We have presented a new technique for object segmentation based on color. We define the notion of probabilistic histograms and certainty measure, used to separate the histograms of two objects simultaneously present in one image. These notions have been compared to standard histogram or normalized histogram techniques. The result shows the superiority of the certainty color map method by a factor 2 on average and proves the interest of this approach.

Certainty color maps have been successfully used in applications like action recognition (simple “take”, “push”, “pull” actions performed in front of a camera). It improves the robustness of previous action recognition systems (see [7]).

5. REFERENCES

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