Morphological Operators for Segmentation of Color Sequences

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Abstract. This paper presents a technique for the segmentation of moving objects in color image sequences. The technique is based on Beucher-Meyer paradigm, with markers detected by a morphological operator designed by computational learning (or, equivalently, statistical optimization.) Objects in some frames of the video are marked manually and used to train the markers detector. Then, the operator designed is used to mark the objects in the other frames and the paradigm is applied to all frames marked by the detector. Two real world examples illustrate the application of the proposed technique.

1 Introduction

A *digital video* is an ordered sequence of digital images, called *frames*. The order is defined by the instant the frame was taken, for instance: frame 1 is the image taken at the instant t_0, frame 2 is the image taken at instant $t_0 + \Delta t$, frame 3 is taken at $t_0 + 2\Delta t$, and so on.

This paper presents an extension of a technique used to segment moving objects in grayscale image sequences [1], for color image sequences. The approach for this problem is based on Beucher-Meyer paradigm, with the markers detector for the moving objects designed by computational learning (or, equivalently, statistical optimization.)

Beucher-Meyer paradigm is one of the most powerful known techniques for image segmentation. The strong quality of this strategy is changing problems of edges detection into problems of marker's detection (i.e., finding a small connected component inside the object to be segmented), that usually is much simpler. The detected markers are used as reference for filtering the gradient of the input image and, finally, the watershed gives the exact (without blur) edges of the objects desired.

In spite of the evolution due to the paradigm, still persists the problem of having a systematic approach to design operators to detect markers. An alternative is to design these operators by computational learning [2].

The proposed technique consists of designing an operator that perform tracking of objects (or, equivalently, detect markers) by training it with some few frames of the sequence and applying the designed operator to the other frames. Having marked the objects in all frames, Beucher-Meyer paradigm is applied for detecting their edges.

A condition for applying this technique is that the training frames be statistically similar to the other frames where the objects appear. When a set of frames with different statistical characteristics appear in the sequence, due to changes in image illumination, resolution, camera position, etc., a new training is necessary before processing the next frames.

There are two advances to the work with grayscale images: (a) the extension of the operator's design to color images, which is done by using the information from a window in each color band of the image and applying the usual design for this larger window (the concatenation of the color band windows); (b) the application of the segmentation paradigm to color images, which is done by using a

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color gradient which enhances the edges of color images but whose result is a grayscale image, where the paradigm is usually applied.

Following this Introduction, Section 2 introduces the operators for color image classification, Section 3 presents a new color image gradient, Section 4 reviews Beucher-Meyer paradigm, Section 5 describes the methodology, Section 6 shows the application of the proposed technique on real world images. Finally, Section 7 gives some conclusions and future steps of this research.

The sequences are composed by color images and they cannot be shown here appropriately. The color results of the described experiments are available in our web site: http://www.vision.ime.usp.br/demos.

2 Color Image Operators for Classification

The main concepts to be introduced in this section are the basis of the methodology for finding markers for color image objects. These concepts are an extension of the concepts used for finding markers for graylevel image objects explored in a previous paper [1].

Let L_1, L_2. ..., L_m be totally ordered complete lattices (also called chains) [3]. For instance: a subset of $\mathbb{Z}$, or a closed subset of $\mathbb{R}$ are chains. Let L be the Cartesian product of L_1, L_2 ..., L_m, i.e., $l \in L \iff l = (l_1, l_2, \ldots, l_m), l_i \in L_i, i = \{1, \ldots, m\}$.

Let E be a non empty set that is an Abelian group with respect to a binary operation denoted by $+$. A mapping f from E to L, $f(z) = (f_1(z), f_2(z), \ldots, f_m(z))$, $f_i : E \to L_i$ and $z \in E$, is called a *multivalued* or *multispectral* image. The mappings f_i are called *bands* of the image. A color image is an example of a multivalued function where $L = L_1 \times L_2 \times L_3$ is the representation of the colors under a certain color model [4]. From now on, let L_1, L_2 and L_3 be three generic chains and L be their Cartesian product.

Let Fun$[E, L]$ and Fun$[E, M]$ denote the set of all mappings from E to L and, respectively, from E to M. A *Color Image Operator for Classification* is an operator from Fun$[E, L]$ to Fun$[E, M]$, where M is a chain. This operator is useful to label color objects and it will be called by simplicity *markers detector*.

Let $W = \{W_1, W_2, W_3\}$, where $W_i \subset E, i = \{1, 2, 3\}$. For any color image f, the *restriction* of f to W is a color image window f/W given by, for any $z \in W$, $(f/W)(z) = (f_1/W_1(z), f_2/W_2(z), f_3/W_3(z)) = (f_1(z), f_2(z), f_3(z))$. For any $f \in Fun[E, L]$ and $x \in E$, the translation of f by x is the function f_x given by, for any $z \in E$, $f_x(z) = f(z - x) = (f_1(z - x), f_2(z - x), f_3(z - x))$.

The *restriction class* of f to W, denoted $\mathcal{F}_{f/W}$, is the family of images whose restriction to W gives f/W, that is, $\mathcal{F}_{f/W} = \{g \in Fun[E, L] : f/W = g/W\}$.

A color image operator Ψ is called *spatially locally defined* in the window W if and only if (iff), for any $f \in Fun[E, L]$ and $x \in E$, $\Psi(f)(x) = \Psi(g)(x), \forall g \in \mathcal{F}_{f_{-x}/W}$. An image operator Ψ is called *spatially translation invariant* iff, for any $z \in E$, $\Psi(f_z) = \Psi(f)_z$. An operator that is both spatially locally defined in W and spatially translation invariant is called a *W-operator*.

A *characteristic function* is a mapping from $Fun[W, L]$ to M. An important property of a W-operator is that it can be characterized uniquely by a characteristic function, that is, there exists a bijection between the set of W-operators and the set of characteristic functions [5, 6]. The characterization of a W-operator Ψ by its characteristic function ψ is given by, for any $f \in Fun[E, L]$ and $x \in E$, $\Psi(f)(x) = \psi(f_{-x}/W)$.

The statistical design of color image operators for classification from image realizations requires estimation of the characteristic function from sample image data (pairs of observed and ideal images) and their representation in an efficient computational form. The statistical design of these operators and their computational representation are very similar to the design of aperture filters which has been treated in a previous paper [7]. The main differences are: W operators are used instead of aperture operators, i.e., the range restriction is not used; a window is used for each band and this information is concatenated in the RGB order to form a pattern that will be used to design and apply the operator.

3 Gradient Operators for Color Images

An important step in morphological segmentation is to find a way to differentiate a pixel from its neighbors based on their grayscales or colors. For grayscale images the *Morphological Gradient* does the job. The problem is more difficult for color images. Even though L can be seen as a complete lattice, the imposed order relation between its elements does not reflect well the perception of the human eye. Besides that, the supremum and infimum of two colors l_1 and l_2 ($l_1, l_2 \in L$) may be neither l_1 nor l_2, as in the graylevel range. The alternative solution to this problem is to find a suitable color space and metric to define a color gradient. In this section, we present a family of gradients and discuss its applicability.

Color processing systems require suitable information representation. Usually, this representation is given by a color space, modeled by a coordinate system, where each subspace is related to some color characteristic. Such color space is called *color model*. One point in a given color model is the unique representation of a color.

There are several color models [8] used in digital image processing. Two of the known models are the RGB (*Red*, *Green* and *Blue*) and the IHS (*Intensity*, *Hue* and *Saturation*) systems.

The RGB system is a cube defined as a Cartesian system. This cube is defined by three subspaces related to one of the three primary colors (red, green and blue) and the pure representation of these colors are located in three corners of the cube. The other corners represent the inverse colors cyan, magenta and yellow, plus the white and black.

The IHS system is defined by a coordinate transformation of the RGB system [8]. This color space is composed by three attributes: *Intensity* (holds the luminosity information), *Hue* (describes uniquely a color in its pure form; for example, the red color without any information from other attributes) and *Saturation* (measures the amount of white light mixed with pure colors).

We introduce now a color gradient computation technique which consists of, following the conversion of the original RGB image into IHS, computing a gradient for each color attribute and making a linear combination of them to obtain the gradient. The technique proposed here has the advantage of enhancement of some desired characteristics; for example, it is possible to enhance the saturation information and ignore the hue one.

Let f be a color image in the IHS color model, i.e., $f \in Fun[E, L]$, where $E \subset \mathbf{Z} \times \mathbf{Z}$ and $L = K \times \Theta \times K$, where $K = [0, 1, 2, 3, ..., k-1]$ and $\Theta = [0, 359]$ are the color components of the IHS color space.

Definition 3.1 *Given $g \in Fun[E, K]$, the morphological gradient of g, $\nabla_B(g)$, is given by:*

$$\nabla_B(g) = \delta_B(g) - \varepsilon_B(g), \tag{1}$$

where δ_B and ε_B are, respectively, the morphological dilation and erosion [9, 3], and $B \subset E$ is the structuring element.

Since intensity and saturation are represented by functions in $Fun[E, K]$, their gradients can be computed by ∇_B. However, it is not the hue case, whose representation is given by a function $h \in Fun[E, \Theta]$. In order to compute a gradient for hue, it is necessary to define a metric function for it.

Let $||\theta_1 - \theta_2||$ be the distance between θ_1 e θ_2, $\theta_1, \theta_2 \in \Theta$, given by:

$$||\theta_1 - \theta_2|| = \lfloor \min\{|\theta_1 - \theta_2|, 360 - |\theta_1 - \theta_2|\} \rfloor. \tag{2}$$

where $\lfloor p \rfloor$ means the floor of the value p[10].

The metric introduced above provides values in the range $[0, 180]$. In order to compute the proposed gradient, these values will be normalized to K. Let $m_K : [0, 180] \to [0, k-1]$ be the normalization function.

Definition 3.2 *Given an image $h \in Fun[E, \Theta]$, the angular gradient $\nabla_\Theta(h)$, $\nabla_\Theta : Fun[E, \Theta] \to Fun[E, K]$, is given by, for all $x \in E$,*

$$\begin{aligned} \nabla_\Theta(h)(x) = \; & m_K(\max_{x_i \in \{B_x - \{x\}\}} \{||h(x) - h(x_i)||\} \\ & - \min_{x_i \in \{B_x - \{x\}\}} \{||h(x) - h(x_i)||\}). \end{aligned} \tag{3}$$

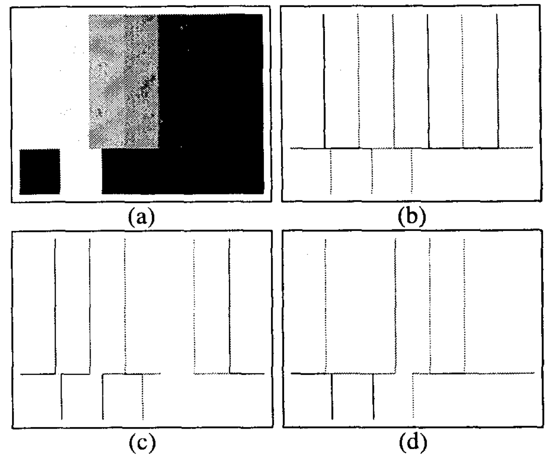


Figure 1: Color gradient. (a) color stripes. (b) color gradient. (c) Enhancing saturation (d) Intensity gradient.

where B is a structuring element centered at the origin of E.

Let μ_a, μ_b and μ_c be three integer numbers. The following gradient is defined as a linear combination of the morphological gradients for I and S with the angular gradient for H. The coefficients of the linear combination are used to enhance or to obscure the peaks of a gradient image.

Definition 3.3 *Given $f \in Fun[E, L]$ in the IHS color model, the color gradient, $\nabla(f)$, $\nabla : Fun[E, L] \to Fun[E, \mathbf{Z}]$, is defined by:*

$$\nabla(f) = \mu_a \nabla_B(f_1) + \mu_b \nabla_\Theta(f_2) + \mu_c \nabla_B(f_3), \tag{4}$$

where f_1, f_2 and f_3 represents the color bands.

The color gradient introduced above is called *sum of weighted gradients*, because each gradient is scaled in order to improve or decrease the weight in the sum. Figure 1 shows an application of this gradient. Fig. 1a is the known color stripes image. Figure 1b is computed assigning the same weight to each band ($\mu_a = \mu_b = \mu_c = 1$). Figure 1c shows the result of increasing the weight assigned to the saturation ($\mu_a = \mu_b = 1, \mu_c = 10$). Figure 1d shows the result of considering only the intensity information ($\mu_a = 1, \mu_b = \mu_c = 0$). The gradient images are inverted for a better presentation.

4 Beucher-Meyer Paradigm

Image segmentation in the context of Mathematical Morphology is usually done by a powerful segmentation method, called Beucher-Meyer paradigm [11]. This method simplifies the segmentation process reducing the problem of segmenting objects directly, to the problem of finding markers for specified objects [12].

Finding the borders of the objects one wants to segment using the operator watershed [13, 14, 15] is the base of the paradigm. A previous preprocessing using connected filters [16] (which do not deform the borders) is usual to prepare the image in order to be segmented. This preparation is useful to eliminate the borders of the objects we are not interested in, and also the borders that appear due to noise in the image.

Borders of colored objects are discontinuities between neighbor pixels in the color space. These borders can be detected using the color gradient presented above. As the graylevel gradient, they are also very sensitive to noise in the image, i.e., they enhance the transitions due to the borders of the objects and also the transitions due to noise. The consequence is that the result of the watershed operator to the gradient image is usually over-segmented [15, 12, 1]. The solution is already classical: to eliminate the borders one does not want by applying an operator that changes the homotopy [9] of the gradient function [11, 12, 1]. After the application of the homotopy change operator on the gradient image, the watershed operator finds only the borders of the objects one wants to segment.

Although the paradigm reduces the problem complexity, finding markers can still be hard. Usually, it is heuristically done.

The proposed alternative to heuristic design of operators to find markers is a method based on computational learning, as discussed in Section 2. One gives pairs of training images (color and labeled frame) to the system and it will design an operator that should be applied to statistically similar color images.

5 Segmentation of Image Sequences

The methodology applied for the automatic design of morphological operators for motion segmentation is simple. Its main steps are (Fig. 2 shows a block diagram of the main steps):

- To train an operator, Ψ, giving some pairs of images $\{f_i, g_i\}$, where f_i is the ith frame of the sequence and g_i is the corresponding marker image. Those images should reflect the different statistical situations in which the objects of interest appear, hence, the indexes i do not need to form a sequence with uniform step like $\{f_i, g_i\}$, $\{f_{i+1}, g_{i+1}\}$, etc. Since one is usually interested on a particular object (or objects) of the image, it is natural that the operator does not need to be trained using the whole image but just some neighborhood of the object(s) of interest. This is done by a mask m_i that will be given to the system together with the training pair $\{f_i, g_i\}$. The mask will restrict the domain where the training samples will be observed to the area inside the mask.

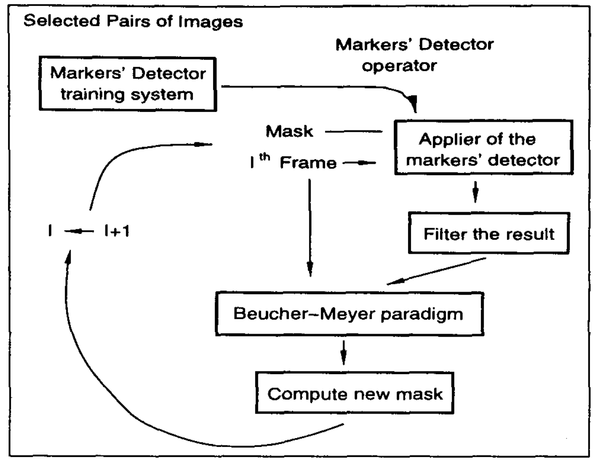


Figure 2: Main steps

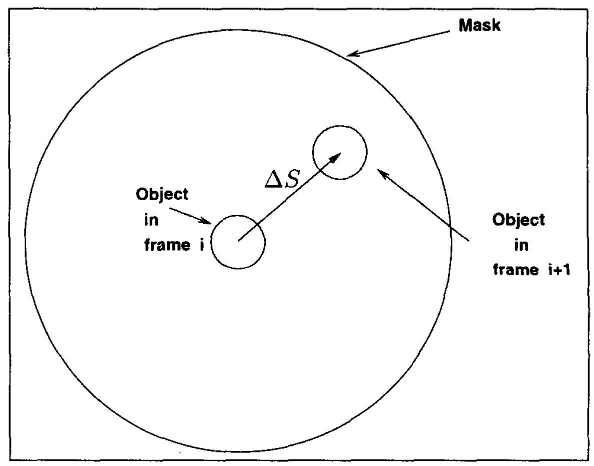


Figure 3: Restriction mask

Figure 3 shows an object in the ith frame f_i and a possible mask m_i used to restrict the learning for the pair $\{f_i, g_i\}$. The radius of the circle that forms the mask is based on a parameter given by the user that reflects the speed of the object in the sequence.

- To apply the operator, the user gives the location of the object in the first frame manually and a parameter related to the speed of the objects in the sequence. The application of the operator is also restricted to a mask but this time the mask m_{i+1} is built from the result of the segmentation of the ith frame f_i plus the speed parameter given by the user (for instance, a dilation by a disk with diameter larger than $\Delta S = V\Delta T$). Figure 3 shows an object in the $i+1$ frame and the respective application mask built from the information of the object segmented in the ith frame.

- To filter the image produced by Ψ. This filter is necessary

to eliminate the markers of low statistical confidence (usually isolated points or small *flat zones*, i.e., regions whose pixels are connected and have the same color). This filter is a composition of a connected filter and a pruning operator [16, 1]. The connected filter is usually parameterized by a structuring element B (to define the connectivity) and its function is to reduce the number of flat zones. The connected filters used in our methodology eliminate the flat zones of area less than a value a specified by the user. This process of eliminating a small flat zone is done by assigning the color of the largest nearest neighbor flat zone to it, or just assigning a standard color to this flat zone. The value a specifies to the system the minimum size of the connected objects that can be considered as a marker, i.e., the system will eliminate the markers smaller than a. The pruning is necessary because the markers resulting after the filtering may cross the borders of the objects.
- To apply Beucher-Meyer paradigm using the homotopy and the watershed operators.

6 Experimental Results

The methodology proposed is applied to two color image sequences. In the first one, we track and segment one billiard ball among seven other ones. In the second one, we segment a pair of hands moving over a cork board.

6.1 Billiard Balls

Our goal in the Billiard Balls sequence is to segment the red ball through the sequence. Figure 4a shows an example of these frames. There are eight balls running through the scene, and each of them has a distinct color. Some of the problems found with this sequence are: luminosity variation in the scene, camera misfocus in the end of sequence, and a large amount of information due to the statistical richness of the domain of color image sequences.

In order to obtain a good generalization when designing the markers detector, the statistical domain of the sequence is reduced by applying connected filters. This filtering reduces not only the number of flat zones in the image, but also reduces the number of colors observed. The used connected filter is a composition of an area opening and area closing to each color band of the image, followed by an operator which merges flat zones whose area are below a threshold. Figure 4b presents the result of this filter applied to Figure 4a.

Two sequences are used to apply our methodology: the original and the filtered ones. Ten pairs of images $\{\{f_1, g_1\}, \ldots, \{f_{10}, g_{10}\}\}$ are used to train the detector. The observation set $\{f_i : i = 1, 2, ..., 10\}$ is taken from the filtered image in order to cover the whole scene; and the elements of the ideal set $\{g_i : i = 1, 2, ..., 10\}$ contain the labels assigned to each ball. A one point window is used to train the operator to track the red ball. It could have been trained to track any other ball in the sequence.

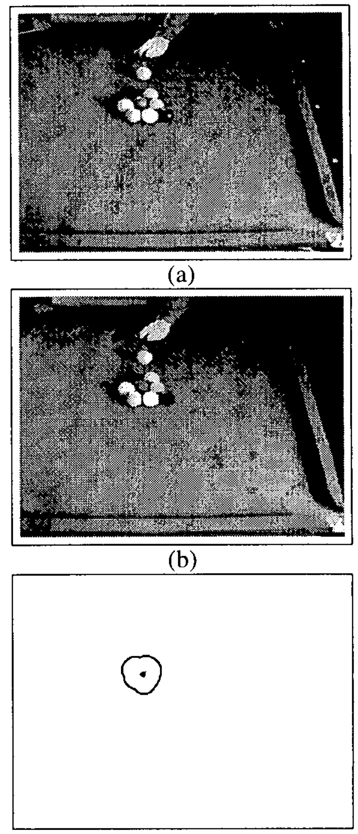

(a)
(b)
(c)

Figure 4: Billiard Ball sequence. (a) Frame of *Billiard Balls* sequence. (b) Filtered frame. (c) Markers.

The tracking step is started with the imposition of the red ball in the first frame, i.e., the ball is manually segmented. In the next steps, the detector is applied to each frame, restricted to a mask given by the dilation of the red ball segmented in the last frame. The result of the detection is the assignment of labels to each ball inside this mask. The marker assigned to the red ball is filtered by a connected filter to suppress the misclassified results. Finally the marker is eroded by a small disk to fit into the desired object. The external marker is obtained dilating the result of the detector and taking its external border. Figure 4c shows the markers used to segment the red ball in Fig. 4a. Finally, the Beucher-Meyer paradigm is applied. Figure 5 shows the watershed line composed with the red ball. The hue information played the main role in the gradient computation since the balls appearing in the scene have distinct colors, but the weighting of the saturation information is important

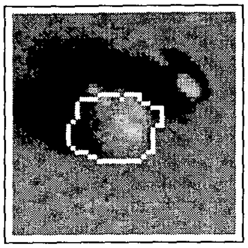


Figure 5: Ball segmented.

to fix details. Figure 6 shows the red ball tracked through 6 consecutive frames. The left column shows a piece of the scene and the right one the watershed lines.

6.2 Moving Hands

The Moving Hands sequence shows a pair of hands moving over a cork board. This sequence is composed by 60 frames in RGB. There is an example of these frames in Fig. 7a. Our goal is to segment both hands. This problem is more difficult than the previous one because: there are two objects to track; each hand is composed of various parts to be segmented, such as the nails and the ring in the right hand.

The strategy of statistical domain reduction by using a connected filter to improve the quality of the designed detector is used. The simplified sequence is provided by application of area opening, followed by area closing (Fig. 7b). This filtered sequence is used to apply the markers detector and to compute the gradient. Ten pairs of images are separated to design the operator. The observation set is composed by frames taken from the simplified sequence while its respective ideal is composed by binary images, assigning value 1 to the hands and 0 to the background.

The segmentation of the first pair is supplied manually. In the next frames, the markers to the hands are obtained via application of the markers detector and filtering its result. This filtering is done by applying a morphological operator composed by connected filters (to eliminate small flat zones) and a thinning operator (to fit the marker into the hands). The external markers are computed dilating the result of the detector. Both internal and external markers are shown in 8a. The color gradient is computed ignoring the hue information and enhancing the intensity and saturation information. Found the markers, the color gradient, the homotopy change and the watershed operator are applied. Figure 8b shows the result of watershed operator composed with the hand.

Figure 9 presents the result of the methodology applied to a selection of a few consecutive frames. The left column shows a piece of the scene and the right one shows the corresponding watershed lines.

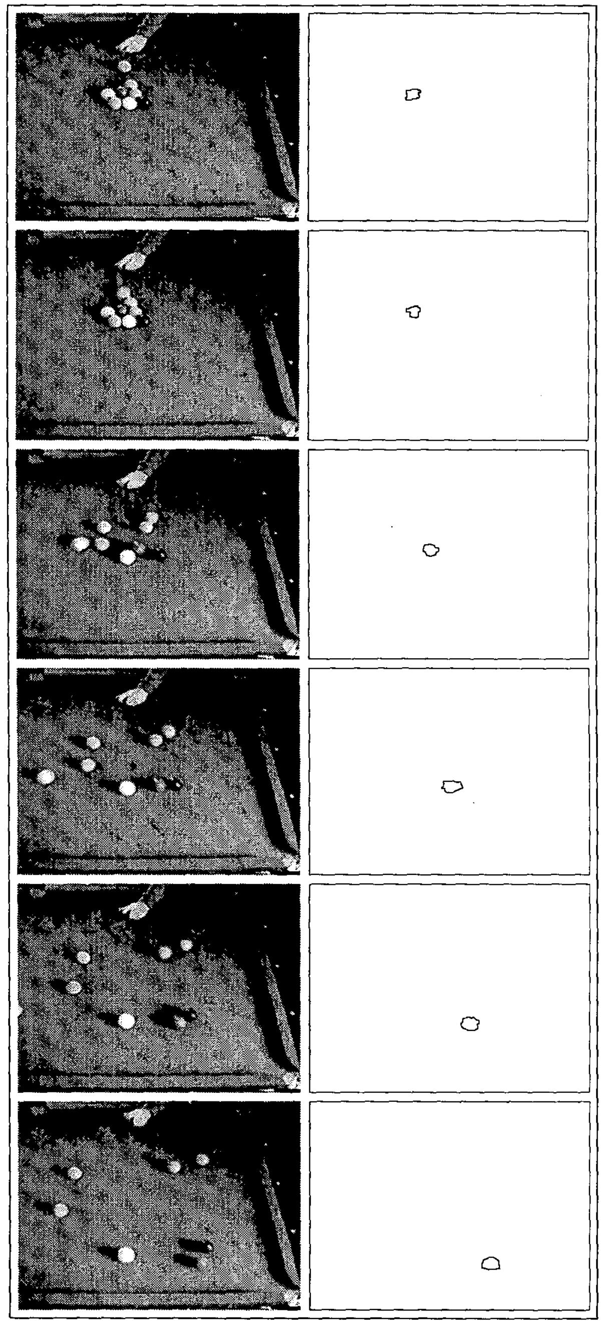
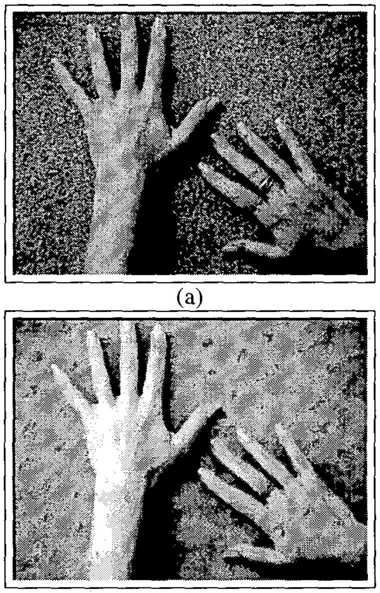


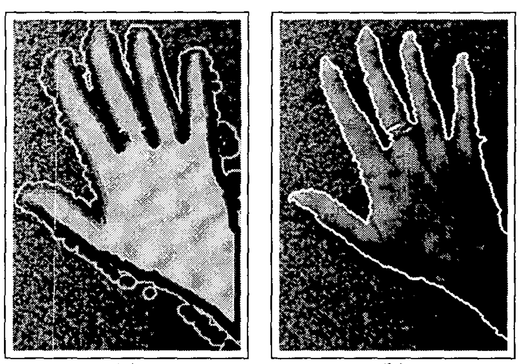
Figure 6: Ball tracked through the sequence.



(a)

(b)

Figure 7: (a) Frame of *Moving Hands* sequence. (b) Filtered frame.



(a) (b)

Figure 8: Results in *Moving Hands*. (a) Markers. (b) Watershed Line.

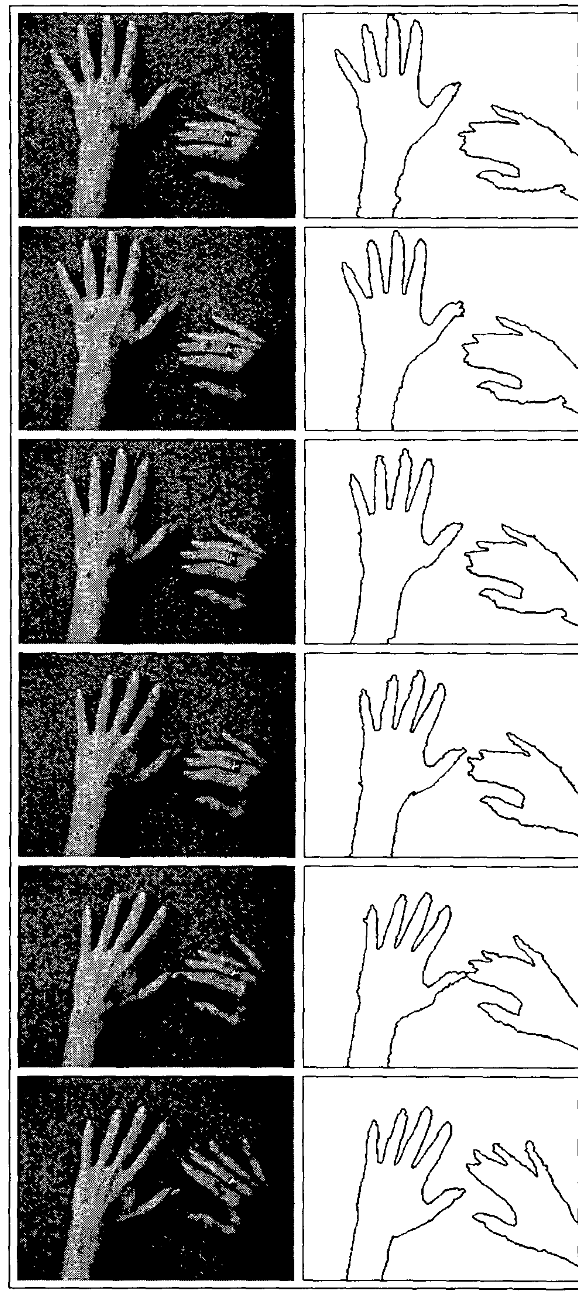


Figure 9: Hands segmented through the scene.

7 Conclusion

This paper extends the design of morphological operators for grayscale sequences [1] in two ways: (i)- it shows how the automatic design of operators can be extended to color images by using the information of the windows for each color band; (ii)- it presents a way to segment color images by Beucher-Meyer paradigm via a color gradient in the IHS color space. The experimental results are outstanding, even when compared to other known techniques we implemented [17, 18, 19, 20]. All the frames have been segmented with very few errors. In the future, we plan to improve the methodology by introducing: a color distance function that reflects better the intuitive notion of color distance; a movement continuity model to avoid the apparent flickering of the borders from frame to frame.

8 Acknowledgments

The first author acknowledges support from FAPESP (process 9800311-4), the second author from CNPq (process 5712791997-0). The authors also acknowledge Teresa Labarre for the Moving Hands sequence (FAPESP process 9810226-4) and Daniel Dantas for helping acquiring the billiard sequences.

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