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Watershed from propagated markers improved by a marker binding heuristic

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Abstract Watershed from propagated markers is a generic method to interactive segmentation of objects in image sequences. It consists in a combination of classical watershed from markers with motion estimation techniques. In order to improve the watershed from propagated markers technique, this paper introduces a marker binding heuristic. It consists in the imposition of pairs of markers along the border of the object of interest and both markers in a pair, the internal and external ones, must be propagated by the same displacement vector computed from the regions delimited by the pair.

Keywords: watershed, propagated markers, object segmentation, image sequences, binding of markers.

1. Introduction

Object segmentation in image sequences [6,7,13] is the segmentation frame-to-frame of an object which semantics remains unchanged. Such technique have been successfully applied to video edition (*Video Masking*) [5,6,11,13, 15,21], video coding [17,19,22,23,25], video surveillance [9,19] and biomedical imaging [1,20].

There are two categories of techniques to segment objects in image sequences: *automatic* (or *non-supervised*) and *assisted* (or *supervised* or also *interactive*). In the automatic segmentation, the objects are detected automatically in the initial frame and they are tracked in the following frames, through application of motion estimation techniques. In the automatic segmentation there is no intervention by users in the obtained results.

In the assisted segmentation, the user is allowed to intervene in the segmentation process. The user can choose, for instance, the objects to be segmented, how they will be tracked, and he/she has the option to correct and alter the segmentation results.

It was proposed, in a previous paper, the *watershed from propagated markers*, a generic method to interactive segmentation of objects in image

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sequences [7]. This method consists in a combination of the watershed from markers [4, 24] with motion estimation techniques [2, 3]. The segmentation technique is tied to the motion estimation one, since the markers to the objects of interest are propagated to the next frames in order to track such objects.

The watershed from propagated markers presents the following characteristics.

1. Interactivity: the user may intervene in the segmentation results: it must be allowed to the user to add/remove markers, to correct bad segmentation and to choose how the markers will be propagated.

2. Generality: the technique can be applied to any image sequences. It is not necessary any *a priori* knowledge about the sequence.

3. Rapid Response: once a marker is imposed or the propagation is activated, the method must answer quickly.

4. Progressive Manual Edition: the user does not need to "look back" to check the previous segmentation; they are considered done. It is not also necessary to erase all markers imposed to a frame when a bad segmentation occurs; the bad segmentation is locally fixed by adding/removing markers to this region.

The proposed method consists in the imposition of markers to the objects of interest in the current frame, given their computation from the segmentation results in the previous frame and their propagation to the current frame, in order to adjust them to their respective objects.

Each marker is propagated from the previous frame to the current one by a displacement vector given by the motion estimation in the area where the marker was computed.

The computation of the internal (external) markers to an object is done by taking the contour of the erosion (dilation) of the object segmentation result in the previous frame. This contour is broken in short segments, and each segment is a marker belonging to the set of internal (external) markers.

A reasonable assumption about the marker propagation is that two closer markers assigned to the same object should have similar displacement vectors, i.e., both markers should follow the motion of the object. However, there are situations where this does not occur properly for two reasons:

1. a marker, that consists in a short segment, may not provide enough information to estimate accurately its motion;

2. the motion of two closer markers are computed separetely.

In these cases, the motion of these markers may not be coherent, or even wrong.

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This paper presents an improvement to the watershed from propagated markers: *the binding of markers*. It consists of computing pairs of markers along the border, and each pair is composed by an internal marker and an external one. Both markers in the pair must be propagated by the same displacement vector, and this vector is computed by the motion estimation of the area *between* the pair of markers.

The binding of markers provides more information to the motion estimation (both markers *and* the area between them). More, it helps the motion of the pair of markers to follow the motion of the border that crosses the region between them in the previous frame.

This paper is organized as follows: The watershed from propagated markers is proposed and discussed in Section 2. The marker binding heuristic is introduced in Section 3. Several experimental results are presented and discussed in Section 4. Finally, this paper is conclude in Section 5.

2. Watershed from propagated markers

The watershed from propagated markers [7, 8] consists, basically, in the following steps.

1. The objects of interest are segmented by the interactive watershed from markers [18], in the initial frame.

2. Given the mask of the segmented objects, the **contour** of erosion of the object and the **contour** of the erosion of the background are obtained. Both contours are broken in short segments forming the set of inner and the set of outer markers to each object.

3. Each segment is propagated to the next frame by motion estimation [10, 14, 16]. These new set of inner and outer markers are used to apply the watershed technique to the next frame.

4. If necessary, the user interacts with the markers, doing the corrections by adding or removing markers, in order to fix the segmentation result.

5. Go to Step 2, until all sequence is processed.

The method proposed above works fine with bad defined contours or strongly textured objects, since the markers are imposed close to the borders of the objects to be segmented. If the quality of segmentation is not approved in some frame, the user can easily move the short-segment marker. The marker propagation is very fast since each segment consists in a few points. Moreover, the contours follow the object deformation, since new markers are created from the segmentation of each frame. The object to be segmented is processed until the end of sequence or until it leaves the scene or be totally occluded. If is partially occluded, it may be possible that the user should intervene to regularize the process.

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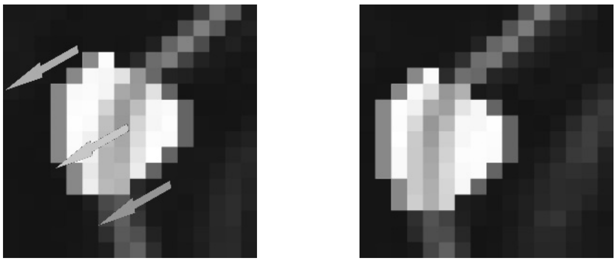
3. The binding of markers

Let us consider a pair of closer markers (one internal and the other external) assigned to the same object. The heuristic proposed here is based on two assumptions:

1. the border of the object to be segmented crosses the region delimited by both markers of the pair (Figure 1(a));

2. the pair of markers must follow the motion of the border.



(a) (b)

Figure 1. Binding of Markers. (a) The internal (right) and external (left) markers delimite a region crossed by the object border. (b) Markers are propagated by the same displacement vector, computing in function of the delimited region.

Considering the above assumptions, both markers of the pair must be propagated by the same displacement vector, i.e., they are propagated to the same direction. For purpose of computing such displacement vector, the region delimited by both markers is considered as a "marker" (see Figure 1(a) - such region is the negated one located between the markers); the displacement vector computed to this region is assigned to the pair of markers. Since it is expected that a region located at the border of the object of interest in frame $k + 1$ gives the best match to the region delimited by the bound markers (Figure 1(b)), such markers should track the border of the object.

Figure 1 illustrates the idea. It shows the morphological gradient of two consecutive frames (both gradients are zoomed). Figure 1(a) shows a pair of markers, an internal (right) and an external (left). The area delimited by the markers was highlighted by negating the gradient at the area. The motion estimation is done considering that area as the marker to be propagated. The displacement vector assigned to this area (as illustrated in Figure 1(a) by the central vector) must be used as the displacement vector of the markers bound to this area (the right and left vectors are exemplified in Figure 1(a)). Figure 2(b) shows the pair of markers propagated to the next frame.

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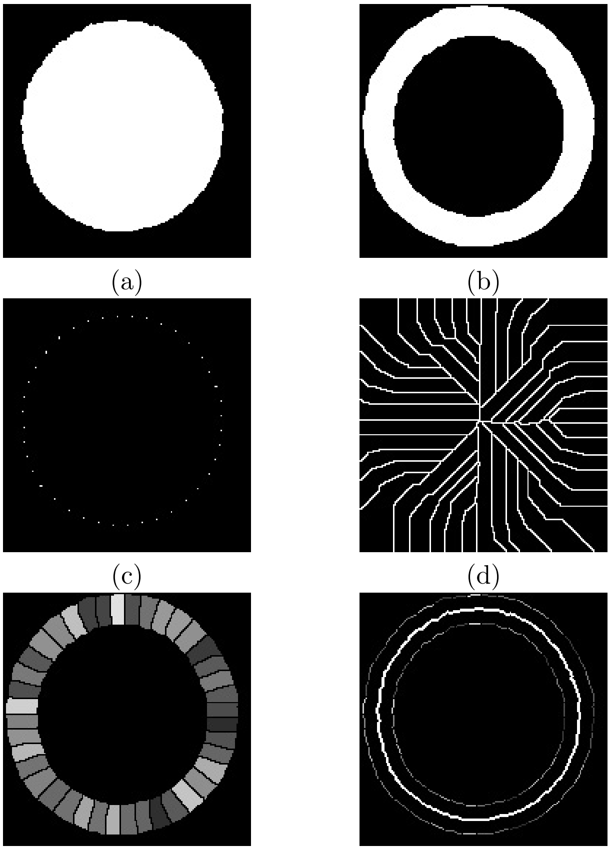

(a) (b) (c) (d) (e) (f)

Figure 2. Creation of the marker pairs and the regions delimited by them. (a) Mask of the segmented object. (b) The "crown" of the mask that must be sliced in order to obtain the delimited regions. (c) The seeds to be used to slice the "crown" of the mask. (d) Watershed lines. (e) Delimited regions (labeled). (f) Pair of markers (labeled) wrapping the borders of the mask.

The pair of markers assigned to the object of interest and the region used to estimate the displacement vector are created by morphological processing of the mask M of the segmented object (Figure 2(a)). Two parameters are required: the distance $\mathbf{m}$ between the internal and the external markers and the width $\mathbf{w}$ of the area.

Let $M_{\delta,\mathbf{m}}$ and $M_{\varepsilon,\mathbf{m}}$ be, respectively, the dilation and the erosion of the mask M by a disk structuring element with diameter $\mathbf{m}$. Both images will be used to compute a "crown", by subtracting $M_{\varepsilon,\mathbf{m}}$ from $M_{\delta,\mathbf{m}}$ (Figure 2(b)).

The next step consists of creating seeds that will be used to separate the regions. Such seeds must be imposed on the contour of M and the geodesic

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distance [12] (started from a point picked from the contour) between them must be $\mathbf{w}$. It is done by labeling the contour of M using the geodesic distance function and by analyzing the division of each label by $\mathbf{w}$; the points which label divided by $\mathbf{w}$ remains zero are the seeds (Figure 2(c)).

The seeds will be used as markers in an application of the watershed operator. The resulting watershed lines (Figure 2(d)) will be used to slice the "crown" of the mask.

The slicing is done by computing the intersection between the negation of the watershed lines and the "crown". Figure 2(e) shows the sliced regions identified by a label (let L be the image which contains the labeled regions).

Given the set of all delimited areas, the creation of the markers is simple. To create the internal markers, just compute the intersection between L and the contour of $M_{\varepsilon,\mathbf{m}}$. To create the external markers, compute the intersection between L and the contour of $M_{\delta,\mathbf{m}}$. Figure 2(f) shows the pair of markers wrapping the borders of the mask M. Each pair of internal and external received a distinct label.

4. Experimental results

This section presents some experiments done with the watershed from propagated markers with the marker binding heuristic and their respective results. The first experiment demonstrates the improvement given by the binding of markers. The second one quantifies the method robustness with several test cases.

4.1 Binding of markers versus no heuristic

The goal in this experiment was to evaluate the improvement of the watershed from propagated markers by application of the marker binding heuristic. Figure 3 shows the propagation and segmentation results achieve by the heuristic.

Figure 3(a) shows the marker propagation by Lucas-Kanade estimation, without adjustment. The length of each marker is $\mathbf{m} = 10$ pixels and the distance of each marker and the border (before propagation) is $\mathbf{w} = 10$ pixels. The result is good except for a few misplaced marker that led to a bad segmentation in some regions (Figure 3(b)).

The heuristic of bind pair of markers provided best results (Figure 4(a)). The fact that both inner and outer markers of the pair were propagated by the same displacement vector avoids the local crossing of the markers (i.e., the internal marker of the pair is not propagated outer than the external one, and vice-versa). More, despite the region between the markers is greater than the markers themselves, it provides more information than the markers without significant loss of performance. The segmentation errors occurred in Figure 4(b) is due the segmentation itself and not due to marker propagation.

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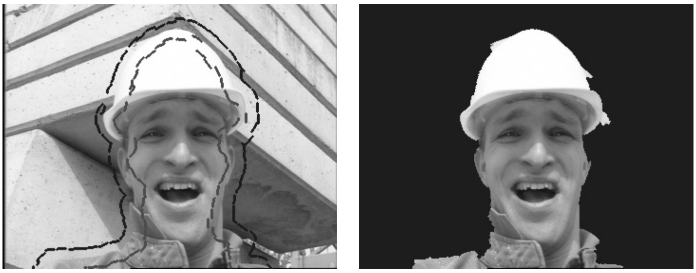
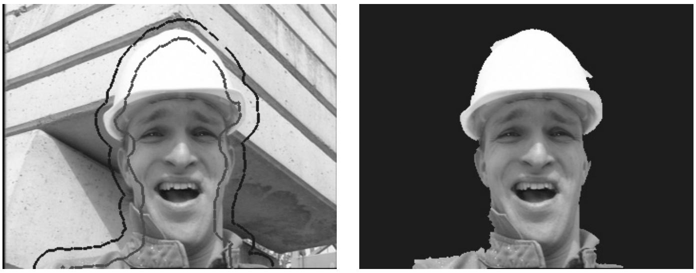


(a) (b)

Figure 3. Heuristic comparison applied to the *Foreman* sequence. (a) No heuristic. (b) Segmentation result.



(a) (b)

Figure 4. Heuristic comparison applied to the *Foreman* sequence. (a) Binding of markers. (b) Segmentation result.

4.2 Robustness

It were done two experiments in order to assess the robustness of the watershed from propagated markers (using the Lucas-Kanade marker propagation and the heuristic of bind of markers).

The results of both experiments were compared to the result of sequence segmented and tracked *manually.* The robustness was assessed by computing, to each frame, the symmetrical difference between the manual segmentation and the segmentation provided by the application of the proposed method in the experiment. The percentage of pixels in the frame that is not zero (i.e., that belongs to the symmetrical difference) is the percentage of segmentation error to this frame.

In the first experiment, the object was segmented and tracked *without* user intervention. The user just insert markers to the first frame and call for propagation until the end of sequence, without marker edition. After the sequence is entirely segmented, the percentage of segmentation error was computed to each frame.

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The second experiment consisted of applying the following instructions to each frame:

1. the percentage of segmentation error for this frame is computed, given the segmentation provided by the markers propagated from the previous frame;

2. the user *intervenes* and edit the markers, in order to correct the segmentation errors in the current frame;

3. the new segmentation of the current frame will provide the markers to be propagated to the next frame.

This experiment was done in order to illustrate the reduction in the percentage of segmentation error, when the user intervenes to correct the segmentation results.

It were segmented and tracked objects in several classical image sequences, and both experiments were done to each sequence. Table 1 shows the percentage of segmentation error in frames 1 to 8 to each sequence. The lines which sequence names are not bold contain the percentage of segmentation error when the method is applied without user intervention (first experiment). The other lines which sequence names are bold show the percentages of segmentation error when the user intervenes (second experiment).

Note that the error in the first frame to all experiments is zero, because, since the object of interest in the first frame is segmented manually, its segmentation result is equal to the segmentation of the same object in the sequence segmented manually. The percentages of segmentation error are the same in the second frame, to each sequence, because the markers provided to the second frame, in both experiments, come from a frame segmented manually. Finally, note the error reduction in each frame, provided by the user intervention in the current segmentation results.

5. Conclusion

In a previous paper, it was proposed the watershed from propagated markers, a generic method to interactive segmentation of objects in image sequences. It consists of computing short segments close to the object borders and apply them as markers propagated to the next frame. The marker propagation is done by motion estimation techniques and the segmentation of the obbjects of interest is done by classical watershed from markers technique. Besides the interactive and the generality, this method also presents two other main characteristics: progressive manual edition and rapid response.

Despite it is expected that two closer markers are propagated by similar displacement vectors, it sometimes does not occur, since the computation of the displacement vectors applied to each of such markers is done separetely

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Table 1. Robustness: Percentage of segmentation error.

Sequence	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Akiyo	0.00	0.85	1.09	0.82	0.95	0.78	0.70	1.20
Akiyo	0.00	0.85	0.95	0.74	0.91	0.76	0.67	0.91
Bream	0.00	0.80	1.72	1.85	0.00	1.98	1.92	1.99
Bream	0.00	0.80	0.61	0.77	1.25	0.59	0.25	0.46
Carphone	0.00	0.66	1.07	1.38	1.90	1.72	1.67	1.67
Carphone	0.00	0.66	0.92	1.31	1.34	1.04	1.38	1.63
Children	0.00	1.14	1.75	2.43	3.18	3.90	5.04	5.19
Children	0.00	1.14	1.31	1.57	1.57	1.93	1.59	2.18
Foreman	0.00	1.31	2.14	2.09	2.39	3.08	3.55	3.83
Foreman	0.00	1.31	2.09	1.15	1.83	1.24	0.98	0.50
Weather	0.00	1.49	1.70	2.36	2.31	2.17	2.26	2.33
Weather	0.00	1.49	1.44	1.52	1.50	1.34	1.28	1.44

or the information provided to the motion estimators is not sufficient to estimate accurately the marker motions.

This paper introduces the *binding of markers*, an heuristic applied to improve the watershed from propagated markers technique. It consists in the imposition of pairs of markers along the border of the object of interest, and both markers of each pair, an internal and an external ones, must be propagated by the same displacement vector, computed in function of the regions located between the two markers in the pair.

The contributions of the marker binding heuristic to the watershed from propagated markers are:

- the increasing in the amount of information provided to the motion estimation, which gives more accurate displacement vectors;

- the easiness for the pair of markers to follow the motion of the border that crosses the region between them in the previous frame.

Several experiments were also done in order to test the watershed from propagated markers with the marker binding heuristic. In comparison to the watershed from propagated markers as it was firstly proposed, the addition of the marker binding heuristic provided better results. It also worked fine when applied to a noisy sequence. Percentages of segmentation error were computed in the robustness experiment and its errors were low.

Future works include the design of more heuristics to boost the marker propagation and the segmentation results. One of this heuristics consists of correcting locally the segmentation result by tightening the pair of markers to the local border of the object.

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