A New Hierarchical Decomposition Applied to Object Segmentation in Image Sequences: The Uniform Decomposition

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***Abstract*—The uniform decomposition is a new hierarchical segmentation method which main property is the preservation of a given characteristic for each subset of the partition provided by the decomposition. Its computation is incremental and, in each iteration, a candidate region is split only if it is found a valid split where each new subset respects an input criterion, for instance size or shape. The uniform decomposition is comparable to the classical one given by the threshold of the extinction values from each regional minima. More, it is comparable while maintaining the criterion for each partition subset. The paper also proposes the application of the uniform decomposition as the core of the watershed from propagated markers, a method applied to assisted segmentation of objects in image sequences. An quantitative evaluation benchmark was applied to assess the combination of the uniform decomposition to the watershed from propagated markers. The evaluation highlights the achievements of good segmentation and efficiency.**

***Keywords*-uniform decomposition; watershed from propagated markers; hierarchical segmentation;**

I. Introduction

Image segmentation is one of most challenging research fields in digital image processing. In consists in the separation of objects contained in an input image by partitioning this image, according to a given criterion or method, in a set of disjoint subsets. Given the representation of objects by each subset of the output partitioning, it is possible to compare and/or classify objects among themselves or just to highlight one object in particular. This case is usually seen as the separation of an object from the background.

Literature presents several methods to do image segmentation. Among them, Mathematical Morphology deserves a mention due to the contribution given by this research field with several operators designed to do image segmentation. In particular, watershed from markers [1] is an efficient segmentation technique, which reduces the problem of segment objects of interest to the problem of find pointers to such objects (these points are called *markers*).

Watershed transform supported by marker selection is also the base for a way to do *hierarchical segmentation* [2]. An image is hierarchically segmented in function of an hierarchy of nested partitions. Through a systematic selection of markers (initially imposed to all regional minima of an image), the segmentation of an image can be refined or coarsened. Hierarchical segmentation makes possible to represent the objects from an image in several levels of details and has been applied to solve problems such as segmentation of MR images [3], cells segmentation [4] and video coding [5].

One way to do hierarchical segmentation is by applying an extinction function [6] to each regional minimum of an image and then discarding all minima which extinction values are lower than a threshold value. It is also possible to segment an image in n most significative regions - according to an extinction function - by taking the regional minima with the n highest extinction values and apply them as markers to the watershed transform.

The method described above is classical under the morphological hierarchical segmentation framework. However, the cited method does not provide a way to control the properties of each subset in a given partition. That method, for instance, makes possible to partition an image in n regions, but nothing can be *globally* stated about any subset of the partition. It could be interesting to have an hierarchical morphological segmentation where each subset of the partition should respect a given criterion, such as size or shape. It could be useful, for instance, in situations where the subsets of the partitions should stand after an area filtering or a erosion by a given structuring element.

This paper introduces a new hierarchical segmentation method that computes partitions with all of its subsets respecting a given criterion: the *uniform decomposition*. The computation of this decomposition is incremental and, in each iteration, a candidate region is split in two new ones only if both new regions are approved by a criterion function. In that way, the method guarantees that all regions in the decomposed image respect the input criterion. Besides this criterion and the input image, the uniform decomposition receives as input data a numerical parameter to the criterion function and a domain of application that makes possible to decompose only a specific region of the image.

This paper also proposes the application of the uniform decomposition as a support method to the watershed from propagated markers [7]. It is an interactive method to object segmentation in image sequences, that combines the watershed from markers technique [1], [8] with marker propagation by motion estimation. The idea is to provide to the segmentation framework a set of markers that leads to good segmentation results and to the reduction of user intervention. Such markers are robust, more consistent and easily edited. An quantitative evaluation was done in order to show the improvement of the watershed from propagated markers given by the support of the uniform decomposition.

This paper is organized as follows: Section II introduces the uniform decomposition. Section III present the variation of the watershed from propagated markers based on uniform decomposition. Section IV discusses experimental results given by the application of the proposed segmentation method to the *Foreman* sequence. Finally, Section V concludes the paper.

II. The Uniform Decomposition

This section introduces the uniform decomposition, some of its properties and its algorithm as well. In order to define the uniform decomposition, some auxiliary concepts must be defined *a priori*.

A. Preliminary Concepts

Let $E \subset \mathbb{Z} \times \mathbb{Z}$ be a rectangular finite subset of points. Let $K = [0, k]$ be a totally ordered set. Denote by $Fun[E, K]$ the set of all functions $f : E \rightarrow K$. An *image* is one of these functions (called graylevel functions). Particularly, if $K = [0, 1]$, f is a binary image. An *image operator* (*operator*, for simplicity) is a mapping $\psi : Fun[E, K] \rightarrow Fun[E, K]$.

Let $N(x)$ be the set containing the *neighbourhood* of x, $x \in E$. We define a *path* from x to y, $x, y \in E$ as a sequence $P(x, y) = (p_0, p_1, ..., p_n)$ from E, where $p_0 = x$, $p_n = y$ and $\forall i \in [0, n-1], p_i \in N(p_{i+1})$.

A *connected subset* of E is a subset $C \subset E$ such that, $\forall x, y \in X$, there is a path P entirely inside C.

The *criterion function* is a function that will be applied to assess connected subsets according to a given criterion `crit` and a parameter p. Its general formula is given by

$$\mathbb{C}_{\texttt{crit}}(C, p) = \begin{cases} 1, & \text{if } C \text{ satisfies the criterion } \texttt{crit}, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where $C \subseteq E$ and p is a numerical parameter.

This paper will use two criterion functions : the *area* criterion and the *disc* one. The area criterion function outputs 1 if the area of the connected subset C is greater of equal to p. It is given by,

$$\mathbb{C}_{\texttt{area}}(C, p) = \begin{cases} 1, & \text{if } \#(C) \geq p, \\ 0, & \text{otherwise}, \end{cases} \tag{2}$$

where $\#(C) : E \rightarrow \mathbb{Z}_+$ returns the cardinality of $C \subseteq E$.

The disc criterion function outputs 1 if $C \subseteq E$ stands when erode by a disc s.e. with radius p. It is given by,

$$\mathbb{C}_{\texttt{disc}}(C, p) = \begin{cases} 1, & \text{if } \varepsilon_{B_p}(C) \neq \varnothing, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

where B_p is the disc s.e. with radius p.

A *queue* is a sequential list of $Q = \{q_1, q_2, q_3, \cdots, q_n\}$ of arbitrary elements which main properties are the insertion of elements at the end of the queue (appended to the n-th element q_n) and the removal of elements from the beginning of the structure (only the first element of Q may be removed, i.e., q_1). A queue Q may have, at least, zero elements (in this case, it is an empty queue).

Let $A, B \subset E$ be two disjoint connected subsets. Let $\mathcal{W}_{A,B}(g)$ be the *watershed from markers operator*, which computes the partition of E in function of g, applying A and B as markers. This partition is given by two subsets E_A and E_B, such that

- $E_A \bigcup E_B = E$;
- $E_A \bigcap E_B = \varnothing$;
- $A \subseteq E_A$;
- $B \subseteq E_B$.

Let $D \subseteq E$ be a *domain of validation*. Given a criterion function $\mathbb{C}_{\texttt{crit}}$ and a parameter p, the sets $A, B \in D$ are two *valid markers* if,

$$\mathbb{C}_{\texttt{crit}}(E_A \cap D, p) = \mathbb{C}_{\texttt{crit}}(E_B \cap D, p) = 1, \tag{4}$$

where $E_A, E_B \in E$ are the two subsets that denote a partition of E computed by $\mathcal{W}_{A,B}$. The *validation* concept introduced above will be applied in the decomposition, in order to check if a subset of the hierarchical segmentation may be split in function of a pair of markers. The splitting must only occur if the two new subsets satisfies the decomposition criterion.

The following algorithm is used by the decomposition algorithm introduced in the next subsection. It receives as input data two regional minima [1] $M_a, M_k \in E$, the image gradient $g \in Fun[E, K]$, the domain of validation $D \in E$, the criterion `crit` and its related numerical parameter $par \in \mathbb{Z}_+$. The **Crit** algorithm receives two candidate regional minima and verifies if they compose a pair of valid markers. In order to do this, it applies the criterion function $\mathbb{C}_{\texttt{crit}}$ to both subsets computed by the intersection of the watershed result with the domain of application and sums their results. If the result of the sum is 2, it means that the markers compose a valid pair of markers. The **Crit** algorithm outputs the sum result.

Crit$(M_a, M_k, g, C, \texttt{crit}, par)$;

$w_k \leftarrow \mathcal{W}_{M_a, M_k}(g)$;
$E_a \leftarrow \{x \in E : w_k(x) = 1\} \cap C$;
$E_k \leftarrow \{x \in E : w_k(x) = 2\} \cap C$;

4 **Crit** $\leftarrow \mathbb{C}_{\texttt{crit}}(E_a, par) + \mathbb{C}_{\texttt{crit}}(E_k, par)$;

B. The Algorithm

The **UniformDecomposition** algorithm has the following input data:

- the input image $img \in Fun[E, K]$;
- the subset $D \in E$ that defines the domain of application of the decomposition;
- the criterion `crit`, applied to the iterative splitting of regions; and
- the parameter $par \in \mathbb{Z}_+$ used when the criterion above is applied to.

The algorithm outputs an image $w \in Fun[E, \mathbb{Z}_+]$ containing the image decomposed in one or more subsets. Each subset will receive a distinct label $lbl \in \mathbb{Z}_+$ in order to be uniquely identified.

UniformDecomposition$(img, D, \texttt{crit}, par)$;

1 $w : E \to \mathbb{Z}_+$;
2 $w(x) \leftarrow 1 : x \in D$;
3 $w(x) \leftarrow 0 : x \notin D$;
4 $g \leftarrow \nabla(img)$;
5 $g(x) \leftarrow \max\{g(y) : y \in D\} : x \notin D$;
6 $lbl \leftarrow 1$;
7 InitializeQueue(Q);
8 **if** $\mathbb{C}_{\texttt{crit}}(D, par) = 1$ **then**
8.1 InsertQueue$(Q, 1)$;
9 **end if**;
10 **while** **NOT** EmptyQueue(Q) **do**
10.1 $Elem \leftarrow$ RemoveQueue(Q);
10.2 $C \leftarrow \{x \in D : w(x) = Elem\}$;
10.3 $\mathtt{M} \leftarrow \mathtt{Min}(g) \cap C$;
10.4 $n \leftarrow$ (number of minima in $\mathtt{M}$);
10.5 $A \leftarrow \{M_j \in \mathtt{M} : \mathcal{E}_\Lambda(M_j) \geq \mathcal{E}_\Lambda(M_{j+1}), j \in [1, n)\}$;
10.6 $M_a \leftarrow M_1 \in A$;
10.7 $M_b \leftarrow \varnothing$;
10.8 $k \leftarrow 2$;
10.9 **while** $(M_b = \varnothing)$ **AND** $(k \leq n)$ **do**
10.9.1 **if** **Crit**$(M_a, M_k \in A, g, C, \texttt{crit}, par) = 2$ **then**
10.9.1.1 $M_b \leftarrow M_k$;
10.9.2 **end if**;
10.9.3 $k \leftarrow k + 1$;
10.10 **end while**;
10.11 **if** $M_b \neq \varnothing$ **then**
10.11.1 $lbl \leftarrow lbl + 1$;
10.11.2 $w_i \leftarrow \mathcal{W}_{M_a, M_b}(g)$;
10.11.3 $W_i \leftarrow \{x \in C : w_i(x) = 2\}$;
10.11.4 $w(x) \leftarrow lbl : x \in W_i$;
10.11.5 InsertQueue$(Q, Elem)$;
10.11.6 InsertQueue(Q, lbl);
10.12 **end if**;
11 **end while**;
12 **UniformDecomposition** $\leftarrow w$;

The **UniformDecomposition** algorithm is described as follows: Lines 1-3 are three abuses of notation. They are done in order to describe the initialization of the output image w. Line 1 states that w is an image belonging to the set $Fun[E, \mathbb{Z}_+]$. In Line 2, w receives the label "1" in all points inside the the domain of application. Outside the domain of application, w receives the value zero. It is done in Line 3 and it means that the region outside the domain does not belong to the result of the decomposition. In the cases when the domain of application is the entire image, w does not receive zeros in any point.

Line 4 computes the gradient of the input image. Line 5 presents another abuse of notation: it means that g will receive the highest value of the gradient in all points outside the domain of application, in order to suppress all regional minima outside that domain.

Line 6 initializes lbl with "1" - the last label assigned to w. Line 7 initializes the queue Q - at this point, Q is empty. Line 8 tests the domain of application itself: if if does not pass the criterion function, the domain must not be split and the algorithm outputs the domain of application labeled with "1". If the domain pass the criterion function, its label must be inserted in the queue - this insertion is done in Line 8.1.

The **while** structure in Lines 10 to 11 controls the iterations of the decomposition. While the queue stores any element, a new iteration must start. Line 10.1 removes a label from the queue and stores it in $Elem$. Line 10.2 computes the region C by taking all points in w which have label $Elem$. Region C is used both as the current domain of validation and the region to be split if a valid pair of markers is found in the current iteration.

Line 10.3 computes the set of all regional minima inside C and Line 10.4 stores in n the number of regional minima in $\mathtt{M}$. Line 10.5 takes all minima in $\mathtt{M}$ and puts them in a decreasing ordered sequence A, according to them extinction values [6]. Lines 10.6 to 10.8 initializes the identifiers involved in the search of a valid pair of markers: Line 10.6 puts the minimum with the greatest extinction value in M_a. Line 10.7 initializes M_b as the empty set: it means that, at this point, it was not found any marker that composes a valid pair of markers with M_a. Line 10.8 initializes k with two, in order to start the check of the minima in A from the minimum with the second greatest extinction value.

The **while** structure in Lines 10.9 to 10.10 searches for a marker in $A \setminus \{M_1\}$ that composes a valid pair with M_1. Line 10.9.1 applies the **Crit** algorithm to M_a and $M_k \in A$ (the k-th element of A) in order to verify the validation of the pair. If **Crit** outputs 2, then the pair is valid and M_b

will denote M_k (Line 10.9.1.1). Line 10.9.3 increments k. If the execution returns to Line 10.9 and $M_b \neq \varnothing$, then the execution of the **while** structure halts and goes to Line 10.11. If the execution returns and M_b is still the empty set, but the k value is greater than n, in Line 10.9, the execution also halts and goes to the Line 10.11.

If, at the current iteration, the execution reaches Line 10.11 and M_b is still the empty set, it means that no valid pair of markers was found and the execution must skip Lines 10.11.1 to Line 10.12. If M_b denotes another marker, the **if** block in Lines 10.11 to 10.12 is executed. Line 10.11.1 increments lbl in order to get the new label to be assigned to w. Line 10.11.2 applies the watershed from markers operator and partitions the image in function of the valid pair of markers. Line 10.11.3 intersects the partition computed in the previous line with C in order to get the region W_i where w will be updated with the new label lbl. A new abuse of notation occurs in Line 10.11.4, where the update occurs: w receives the label lbl just in the region given by W_i. Finally, Lines 10.11.5 to 10.11.6 inserts $Elem$ and lbl in Q, in order to process the regions labeled by them *a posteriori*. Note that, in the iterations where the **if** block is not executed, the length of the queue decreases in one unit. That is the way that the queue may be empty and makes possible the algorithm reaches the end, outputing w in Line 12.

III. Uniform Decomposition and the Watershed From Propagated Markers

The watershed from propagated markers [7] is an assisted method to object segmentation in image sequences, given by the combination of the classical watershed from markers technique [1], [8] with motion estimation. The objects are segmented interactively in the first frame and the mask generated by its segmentation provides the markers that will be used to track and segment the object in the next frame. Besides the interactivity, the proposed method has the following important characteristics: generality, rapid response and progressive manual edition.

The first proposal of the watershed from propagated markers computed short segments close to the border of the objects and applied them as markers. An improvement to this technique was proposed in [9] : the *binding of markers*. It consists in the computation of 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. This heuristics provides more information to the motion estimation and 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.

In the following, we introduce a new variation to the watershed from propagated markers technique. In this variation, the watershed from propagated markers is improved by application of the uniform decomposition, which is applied to compute the set of inner and outer marker.

1) The spatio-temporal gradient [10] is computed for the entire sequence.
2) The objects of interest are segmented by the interactive watershed from markers (Fig. 1 (a) shows the current frame where the *Foreman* will be segmented).
3) The mask of the segmented object defines the domain of application D_f which is the region where the uniform area decomposition will be applied to (Fig. 1 (b)). Let $\texttt{crit}_f$ and par_f be the criterion and parameter assigned to the foreground. The partition of D_f results in a set of pre-markers P_f assigned to the object of interest.
4) Many subsets of P_f do not touch the border of the segmented object and they can be discarded since the remaining pre-markers suffice to track the object, since they are close the object border. The set of internal markers M_f to be assigned to the object of interest is given by the remaining pre-markers (Fig. 1 (c)).
5) Consider the negation of the segmentation mask as the domain of application D_b and the criterion $\texttt{crit}_b$ with parameter par_b assigned to the background. Apply the same procedures described in Steps 2 and 3 to the background, considering D_b, $\texttt{crit}_b$ and par_b in order to compute the set of external markers M_b (Fig. 1 (d)).
6) The markers in M_f and M_b are propagated by application of the Lucas-Kanade technique [11], taking into account the current and the next frames. Given a marker M from M_f or M_b, its motion vector is computed considering the entire region defined by M. However, the marker propagated to the next frame is given by the erosion of M by a disk structuring element, which diameter is a velocity parameter (Fig. 1 (e) and (f)).
7) The collision of different kind of markers, which may lead to bad segmentation results, is solved by computing the symmetrical difference among the two sets of markers, dilating this difference and subtracting it from both sets M_f and M_b.
8) Go to the next frame and apply the propagated markers (Fig. 1 (g)) to segment the initial mask to this new frame (Fig. 1 (h)). The segmentation is done by application of watershed from markers, imposing the propagated markers to the spatio-temporal gradient from the new current frame. If necessary, the user improves the segmentation results by interacting with the markers.
9) Go to Step 2, until the sequence is fully processed.

The uniform decomposition is applied to the watershed from propagated markers framework in order to compute larger and more consistent markers. It presents several advantages:

- The markers tends to stand the erosion done in function of the velocity of the objects - if the parameters are set correctly.
- Since the size of the markers tends to be larger than the ones in previous versions of the watershed from markers, it will provide much more information to the motion estimator. Besides the size, the region in the marker location is also more homogeneous.
- Since one marker tends to represent one object in the scene, Lucas-Kanade motion estimation is a good choice to do marker propagation, because it assumes that the motion inside a region is constant.
- The markers are larger and tight to the object border, what improves the segmentation results when they are well propagated.
- If a marker is not well propagated, its size makes easier the task of edit or remove the misplaced marker.
- The interactive hierarchical segmentation may be easily integrated to the interactive step of the watershed from propagated markers, when the user interferation is called.

IV. Experimental Results

The experiment described below shows a quantitative assessment of the segmentation of *Foreman* sequence by manual segmentation and by application of the watershed from propagated markers. This assessment is done by application of the benchmark proposed in [12] which assess several features such as number of user interventions, time to segment the sequence and amount of motion. The experimental results can be watched in the videos available at the website:

http://calhau.dca.fee.unicamp.br/wiki/index.php/

Several authors use the *Foreman* sequence to demonstrate the performance of their methods, from video coding [13], [5], [14] to sequence segmentation techniques. Unfortunately, it is hard to do a fair comparison between our method and many other important ones that segment *Foreman* because their great majority consists in automatic segmentation methods.

Foreman is a very interesting sequence because it presents many important test situations. The foreman himself, for instance, while he appears in the scene, moves his head in many directions (left, right and forward and backward, what provides a zooming sensation of the foreman face). Foreman head sometimes rotates, what gives a kind of deformation of the object of interest. Camera is also moving in a smooth but uncontrolled way. If the foreman is the object of interest, note that he is composed by several objects that need to be segmented and tracked: the helmet, his face and jacket. Besides, the sequence presents several regions of low contrast such as the foreman shoulder, his ears and the region where helmet meets the white concrete background. *Foreman* sequence is not a trivial task to segment appropriately.

The experiment consists in evaluating two methods applied to segment the man in the first 150 frames of *Foreman*:

- The manual method;
- The watershed from propagated markers with uniform decomposition support and **Lucas-Kanade motion estimator**;

Figure 3 presents - in magenta - the motion information of *Foreman* sequence, given its ground truth segmentation. Foreman appears to move in a reasonable velocity in almost the entire sequence (note that the difference between consecutive frames is about 1.5% in most frames. The mean error between consecutive frames is 1.7652%). The exceptions are in the end of the sequence where the foreman appears to move quickly and in the frame **90**, where the hand of the foreman appears in the scene, disappearing in the next frame. This fact can be also observed in the assessment of the second method - see Fig. 3 (c).

The ground truth is given by the manual segmentation of *Foreman* sequence. It was necessary 3990 user interferences - mean of 26.6 interferences for frame - to do the manual segmentation (Fig. 3 (a) in magenta). The total time spent to do all segmentation was 12266 seconds = 3.4073 hours (Fig. 3 (b) in magenta). Note in Fig. 3 - in magenta - that the number of interferences and the time spent for frame is higher at the end of the sequence, because the foreman moves more quickly in that instant.

The second experiment was done with the application of the watershed from propagated markers - supported by the uniform decomposition and Lucas-Kanade motion estimator - which results are shown in Fig. 2. Figure 3 (a) and (b) show, respectively, the amount of interference required and the time spent to segment the foreman in each frame (in black). The last experiment required 80 interventions (mean of 0.5333 interventions for frame) and it was accomplished in 1001.6 seconds = 16.6927 minutes (mean of 6.6771 seconds each frame). Again, note the intervals in the sequence where intervention was not needed (Fig. 3 (a)). Also note that the segmentation of the foreman at the end of the sequence is still critical and required a lot of intervention.

Segmentation error for each frame, is shown in Fig. 3 (c) - in black. Error due the misplacement of propagated markers was reduced and the segmentation of some critical regions was improved, but there still appeared some bad segmentation in several critical points that required intervention. Mean segmentation error occurred due application of the watershed from propagated markers - *Lucas-Kanade motion estimator* - was 1.6434% for each frame.

V. Conclusion

The uniform decomposition is an hierarchical segmentation method which main property is the preservation of a

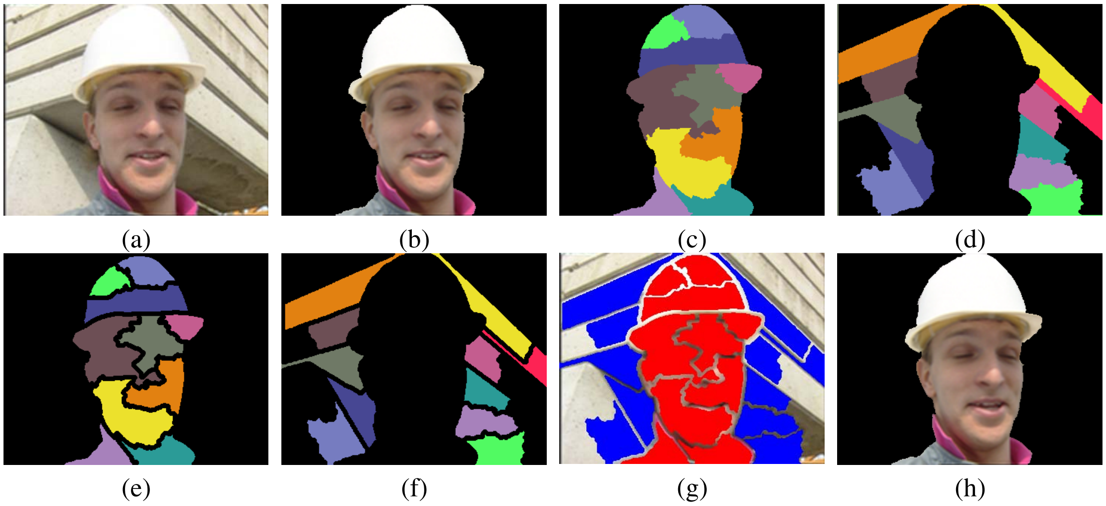

Figure 1. Uniform decomposition applied to the watershed form propagated markers framework. (a) Current frame. (b) Composition with the segmentation mask D_f. (c) Set of inner markers M_f. (d) Set of outer markers M_b. (e) Erosion of markers M_f. (f) Erosion of markers M_b. (g) Inner and outer markers propagated and overlaid in the next frame. (h) Segmentation in the next frame.

given feature for each subset from the partitioning computed by the decomposition. It is an incremental method where, in each iteration, a candidate region is broken in two subsets that preserve criteria such as size or shape. The uniform decomposition outputs an image partition such that all subsets from this partition have the applied input criteria. In other words, no one partition subset, measured according to the chosen criterion, has the measured value lower than a numerical parameter related to the criterion.

This paper introduces the uniform decomposition and its application to a variation of the watershed from propagated markers framework. This variation is based on the computation of inner and outer markers by application of the uniform decomposition. Such markers are bigger, consistent and homogeneous and provide a different way to interact with the segmentation results that have, usually, a good quality.

The markers generated by the uniform decomposition are more consistent because this hierarchical segmentation allows the control of the image decomposition according a criterion. The area criterion, for instance, allows the construction of bigger and homogeneous markers. The disc criterion create markers that resist the erosion with certain disc-shaped structuring elements (i.e., discs which diameter is lower than the disc criterion parameter).

The uniform decomposition is tied to the watershed from propagated markers in this manner: the inner markers are computed considering the mask of segmentation has the domain of application of the decomposition. The subsets of this partition are eroded and propagated. Similarly, the outer markers are computed considering the negation of the segmentation mask as the domain of application, and the subsets are also eroded and propagated. Finally, the inner and outer markers are fixed by the removal of the intersection of different kind of markers.

The benckmark proposed in [12] was applied to assess the watershed from propagated markers supported by the uniform decomposition and motion estimation by Lucas-Kanade method. In this assessment, the foreman was segment from the first 150 *Foreman* sequence frames. It was required, on average, 0.88 user interventions for each frame and all frames was processed in 20.6964 minutes (a mean of 8.2786 for each frame). The segmentation error is some critical regions or due to bad marker propagation was low (mean error or 1.1642% for frame). Some critical points, in some frames, required user intervention.

The variation of the watershed from propagated markers proposed in this paper provides robust segmentation results and with fewer user effort, besides the set of markers that are more consistent and easier to edit. Another contribution of this paper is the uniform decomposition itself, that deserves future developments.

Other applications of the uniform decomposition, such as pre-processing for stereo vision and interactive segmentation - used in the interactive step of the watershed from propagated markers - will be reported in a future work.

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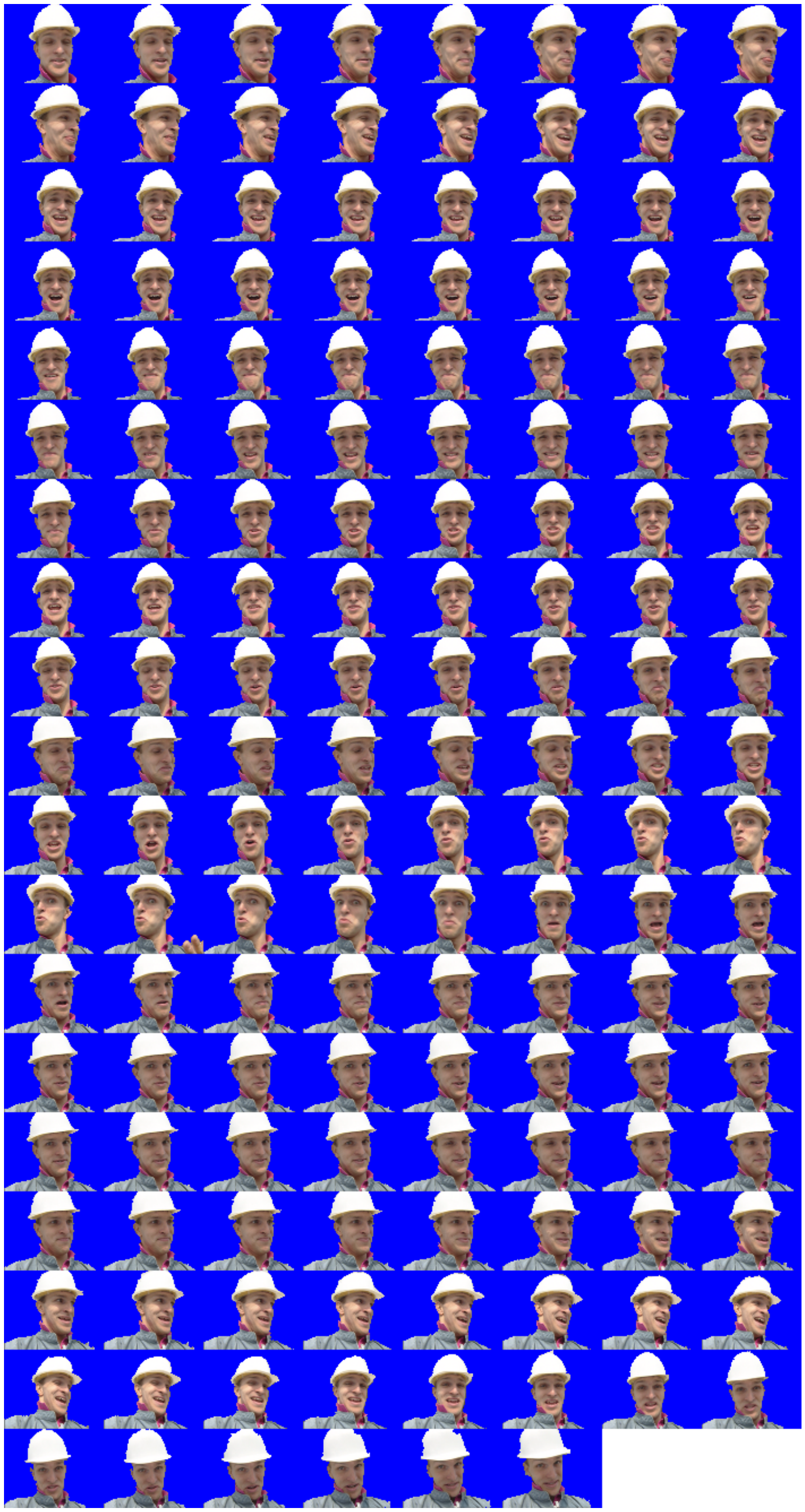
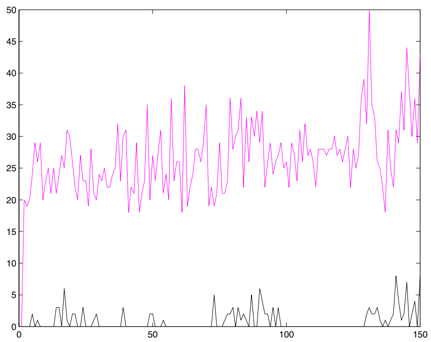
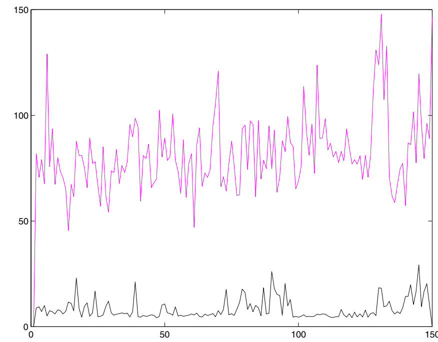


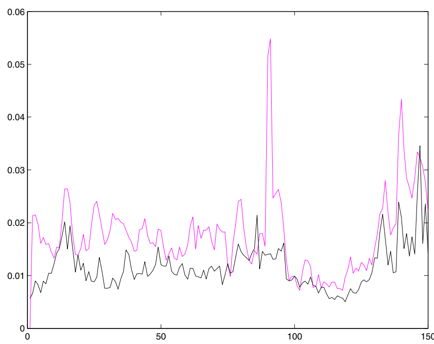
Figure 2. *Foreman* sequence segmentation by watershed from propagated markers - supported by the uniform decomposition and by Lucas-Kanade motion estimation (frames 1 to 150).



(a)



(b)



(c)

Figure 3. Analysis of the *Foreman* sequence segmentation by watershed from propagated markers - supported by the uniform decomposition and by Lucas-Kanade motion estimation. (a) Number of user interventions in each frame (magenta for ground truth segmentation and black for the watershed from propagated markers result). (b) Time spent in each frame (again, magenta for ground truth segmentation and black for the watershed from propagated markers result). (c) Motion information (in magenta) and segmentation error in each frame, compared to the ground-truth (in black).

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