

# Image Segmentation by Image Analogies

Asma Bellili and Slimane Larabi

USTHB University, Computer Science Department,  
BP 32 El Alia, Algiers, Algeria  
slarabi@usthb.dz

**Abstract.** In this paper we propose a new technique for image segmentation based on contour detection using image analogies principle. A set of artificial patterns are used to locate contours of any query image. Each pattern allow the location of contours corresponding to specific intensity variation. Boundaries are extracted based on the properties of located contours. In addition, elementary regions derived from the motion of contours in images are located and combined jointly with the boundaries for image segmentation. Experiments are conducted and the obtained results are presented and discussed.

**Keywords:** Image Segmentation, Analogies, Contour Detection, Multi-Scale

## 1 Introduction

Image segmentation is a preprocessing step whose goal is to express an image in meaningful way and to divide it into spacial regions having some common characteristics. This task which change the representation of an image into something that is easier to analyse is a fundamental process in many computer vision applications.

There are many image segmentation methods proposed in the literature. Many states of the art have been done and published [6] [14] [15] .

A review of the literature in image segmentation indicates that natural images segmentation algorithms can be divided into two categories : Region based and Edge-based approaches. Region based approaches aim to regroup pixels having similar attributes, and the edges-based methods aim to separate regions having dissimilar attributes.

This problem remains an attractive topic for two reasons: the first one is that the results of proposed techniques are still far from what can do the human. The second one is that the segmentation is a critical step for all applications.

Image analogy is a new technique for image processing by example which consist in two steps:

- The first one consist on designating two images  $(A, A')$  such that  $A'$  is the transformation of  $A$  applying a filter.
- Assuming that the transformation between  $(A, A')$  is learned, the second step consist to apply to any given image  $B$  the same transformation  $(A : A')$  giving

the image  $B'$  [7] [10].

Image analogies has been largely used in different applications such as super resolution [8], texture [2] [3] [5], curves synthesis [11], image colorization, image enhancement and artistic filters [16], [17]. An advantage of image analogies technique is the possibility to learn very complex and non linear image filters such as artistic filters in witch various drawing and painting styles are synthesized based on scanned real world examples [10].

Few works have been devoted for the use of image analogies in image processing. A method for supervised segmentation of medical images is proposed by Lackey and Colagrosso [12] applying directly and naively the algorithm of Hertzmann [10]. This method is applied only to find by analogies the same coloured regions in medical images as those processed by the expert. We notice here that the application of naive way to image segmentation like is made in [12] requires numerous pairs of learned images  $(A, A')$  where  $A$  is initial image and  $A'$  is the segmented image. This is due to the requirement of all lighting conditions in learned images.

S. Larabi and N. M. Robertson proposed a method based on the learning of the expertise of hand draw contours to locate outlines of a query image in the same way that is done for the reference [13]. The result of their approach was a set of images which contains several contours, each one is the result of using of artificial pattern instead of hand drawn contours.

In [4], authors proposed a method based on these contours in order to define and locate the outlines of objects. In this work, we propose a method to extract boundaries of objects and then to segment image in regions. The next section is devoted to a brief review of contour detection by image analogies and the inferred properties. Our method is presented in section 3 followed by the results of experiments conducted on Weizmann data set [1] presented section 4.

## 2 Contour detection by image analogies and properties: A brief review

The idea is to start from a pair of images  $(A, A')$ ,  $A$  is an initial image and the second one  $A'$ , identical to  $A$ , in addition, contours are hand drawn. The aim was to localize the contours of any other query image  $B$  using the expertise learned from the pair  $(A, A')$  (see figure 1)[13].

A set of artificial patterns are proposed instead of hand drawn contours in images as learning images (see figure 2). The use of these patterns allow locating fourteen images of contours. Each one is obtained by the corresponding pattern  $(A, A')$ .

In [4], authors demonstrated that contours in the 14 images of contours located by image analogies technique are moving from one image to another and are more steady around the boundaries of regions. However, for others parts of the image, they are moving fastly (see figure of table 1).



Fig. 1. Contour detection: The main idea [13]

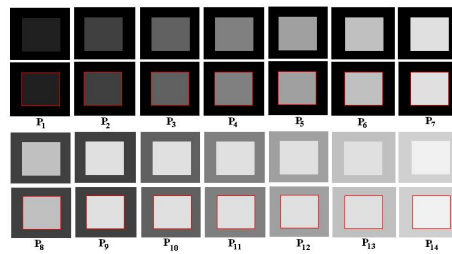


Fig. 2. Artificial patterns used as training images

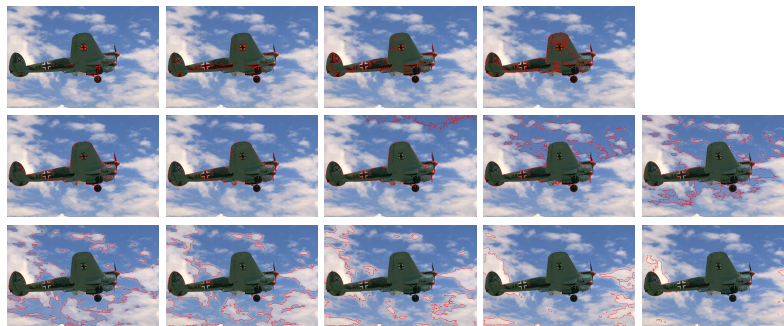


Table 1. Contours located using a selection of the 14 artificial patterns

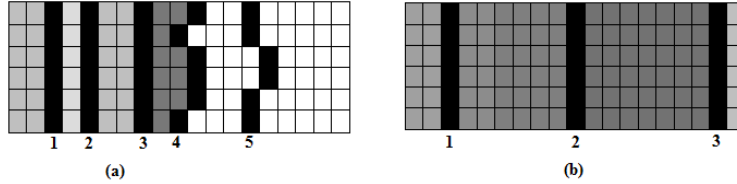
### 3 Image segmentation

#### 3.1 Energy map of pixels

The stability of a contour is measured from its motion in all images of contours. More the motion of the contour is slow, more it will be considered as the region boundaries [4] (see figure 3).

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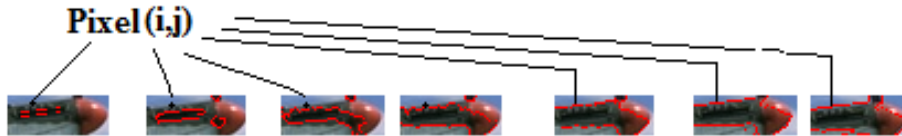
In this section, we propose firstly an algorithm for measuring the stability of a pixel among all images of contours. A map of energy is created from the images of contours and used to locate regions. Also, depending on the energies of pixels, multi-scale segmentation is presented.



**Fig. 3.** (a) Slow motion of contours located using five successive patterns and reported in the same part in image, (b) Fast motion of contours located using three successive patterns and reported in the same part in image

Let  $p_{i,j}^k$  be the pixel  $(i, j)$  in image  $IM_k$  of contours obtained using the pairs of patterns  $P_k, k = 1..14$ . There are 14 images  $IM_k$  and in each one the pixel  $p_{i,j}^k$  may be or not a contour pixel.

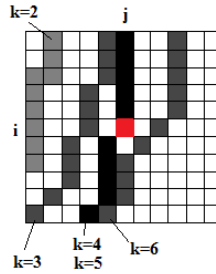
Our aim is to compute an energy map of pixels starting from the set of images of contours. Each pixel  $p(i, j)$  will be associated a value measuring its appartening to a border of region or to inside of region. As explained above, around the pixel  $p(i, j)$  in the image, pixels of contours of all images  $IM_k, k = 1..14$  are moving from the darkest part to the clearest one (see figure 4).



**Fig. 4.** Appearance of the same pixel  $(i, j)$  for different images  $IM_k$  of contours

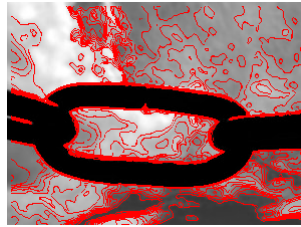
To evaluate the evolution of the contour around  $p(i, j)$  in all images of contours  $IM_k, k = 1..14$ , we consider an area of  $((2N+1) \times (2N+1))$  pixels. For each pixel  $p$ , and for each  $IM_k$ , we search the nearest pixels of contours  $q$  following the  $n$  directions in the defined area. Four directions are considered: Horizontal, vertical and two diagonals directions. The energy of the pixel  $p$  is computed using the distances  $d_k$  of the nearest contour pixel  $q_{i,j}^k$  to  $p$  in the image  $IM_k$ . The energy  $E$  of  $p$  is defined by equation 3.1.

$$E = \sum_{k=1}^{k=14} 2^{N-d_k} \quad (1)$$



**Fig. 5.** Search area of contour pixels for all 14 images. Notice the presence of five contours located using five successive patterns  $k = 2..6$ , two of them pass by  $p(i, j)$

More there are pixels  $q$  nearest to  $p(i, j)$  found in successive images  $IM_k, k = 1..14$ , more the energy  $E$  is highest. However, when there are few (one or zero) pixels  $q$  found, this implies that the energy  $E$  is very low. For example,  $E = 2$  is associated to  $p(i, j)$  in case where there is only one pixel contour located at distance  $(N - 1)$  from the central pixel  $(i, j)$ . However, when there are five contours pixels located (such that illustrated by figure 5), corresponding to the distances  $N - 1, 1, 0, 0, 1$  (moving from the left to right), the energy  $E$  is then equal to  $E = 2^1 + 2^{N-1} + 2^N + 2^N + 2^{N-1}$ , for  $N = 5, E = 98$ . This energy is then synonymous of the appartaining of the pixel  $p(i, j)$  to the inside or to the border of region. The values of energy computed have similar significance like the result of merging of all images of contours giving largest contours at borders of regions and thinnest elsewhere (see figure 6).



**Fig. 6.** Result of merging all 14 images of contours

### The Algorithm

#### Begin

- $(IM_k, k = 1..14)$  are the images of contours located using the patterns  $(A^k, A'^k)$

- $N$  is the distance defining the search area

- $I_m$  is the map of energies to compute

**For** each  $p(i, j)$  of  $I_m$

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Do For each image  $IM_k$   
  Do search the nearest pixel contour  $q$  to  $p(i, j)$   
   $d$ =distance ( $q, p$ ), if  $d < N$ ,  $E(i, j) = E(i, j) + 2^{N-d}$   
  EndFor  
EndFor  
End.
```

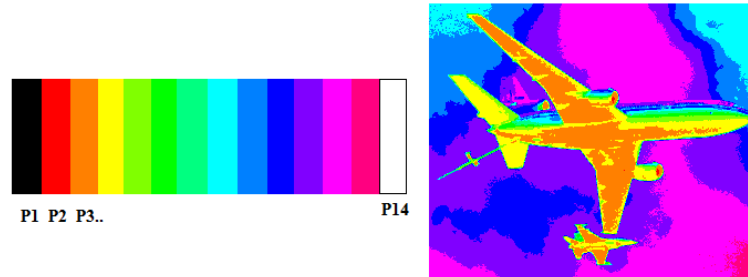
### 3.2 From map of energies to multi-scale segmentation

The different values of energy associated to each pixel define the map of energies end noted  $I_m$ . We used this map to locate the boundaries of regions at different scales: (high, intermediates and low) which correspond to the four intervals of energy:  $[46, 56[$ ,  $[56, 64[$ ,  $[64, 128[$ ,  $[128, \infty[$ . For each value of energy, there are pixels of boundaries which are selected, where strong boundaries are associated to high values of energy. Figures of table 2 illustrate for each image the located boundaries at low, intermediate and high scale.



**Table 2.** For some images of Weizmann data set, boundaries located at low (second row), intermediate (third row) and high (fourth row) scales

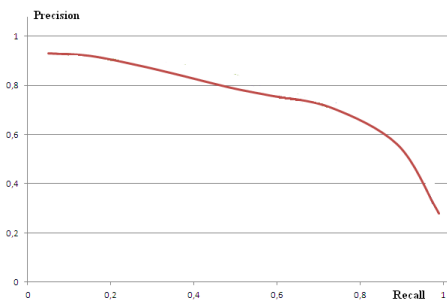
Once the boundaries are located, an additional processing is required in order to achieve the segmentation. Elementary regions defined as the areas between contours located using two successive patterns are firstly located and combined jointly with the located boundaries in order to locate regions in image. Figure 7 illustrates these elementary regions where 14 colors are associated to elementary regions obtained using the 14 artificial patterns.



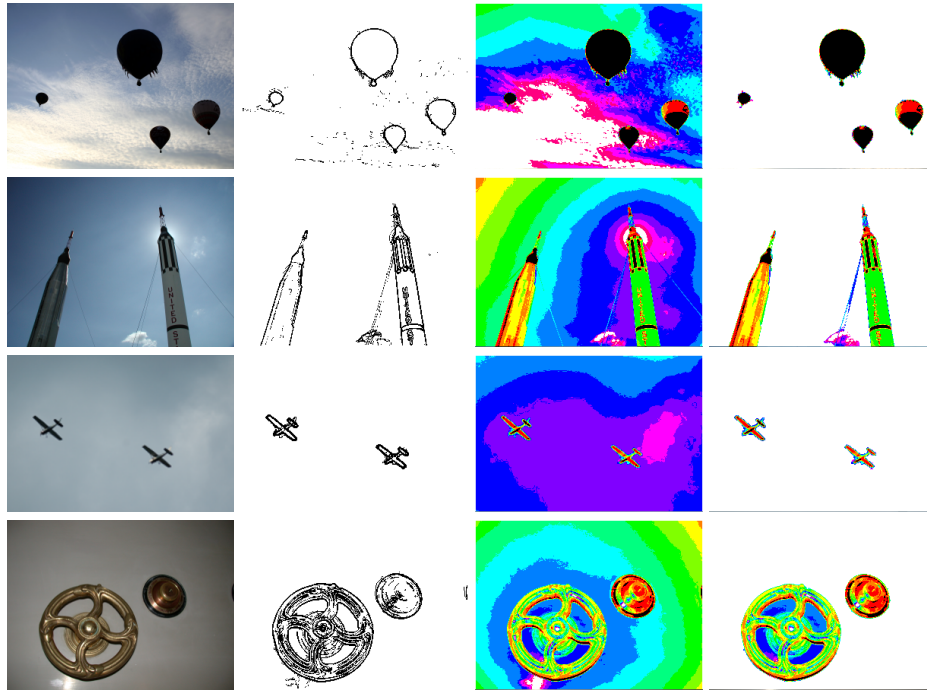
**Fig. 7.** At the left: the different colors associated to elementary regions located using each one of the 14 patterns. At the right, the result obtained for image from Weizmann data set

## 4 Results

In this section we present results obtained by applying our method on Weizmann data set. Figures of table 3 show the boundaries detection of images at high scale, the elementary regions located using the 14 patterns and the result of fusion with computed boundaries. Compared to the ground truth data, we achieved a good values of recall and precision (see figure 8).



**Fig. 8.** Evaluation of the results obtained on Weizmann data set



**Table 3.** For some images of Weizmann data set, boundaries located at high scale, the located elementary regions, the result of fusion process

## 5 Conclusion

In this paper we proposed a new technique for image segmentation based on contour detection using image analogies principle. A set of artificial patterns are used to locate contours in any query image. Each pattern allow the location of contours corresponding to specific intensity variation. Multi-scale boundaries of regions are then extracted based on the energy map derived from the properties of contours located. Elementary regions are also extracted and combined with the boundaries to locate the regions. Experiments are conducted and the obtained results show the efficiency of our method compared to the state of the art.

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