Outlines of Objects Detection by Analogy

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Abstract. In this paper we propose a new technique for outlines of objects detection. We exploit the set of contours computed using the image analogies principle. A set of artificial patterns are used to locate contours of any query image, each one permits the location of contours corresponding to a specific intensity variation. We studied these contours and a theoretical foundation is proposed to explain the slow motion of these contours around regions boundaries. Experiments are conducted and the obtained results are presented and discussed.

Keywords: Segmentation, Object outline, Analogy, Contour, Multi-Scale.

1 Introduction

Image segmentation is considered as an important task in many computer vision applications. It consist of partitioning an image into meaningful regions including objects. Despite that there are many image segmentation methods proposed in the literature [5], [16], this problem remains an active topic for two reasons: first, results of the proposed techniques are still far from what the human can achieve; second, segmentation is a critical step for many applications.

Image analogies constitutes a natural means of specifying filters and image transformations. Assuming that the transformation between two images A and A' is "learned", image analogies is defined as a method of creating an image filter which allows to recover by analogy from any given different image B the image B' in the same way as A' is related to A [6], [9]. Rather than selecting from among myriad different filters and their settings, a user can simply supply an appropriate exemplar (along with a corresponding unfiltered source image) and say, in effect, "Make it look like this". Ideally, image analogies should make it possible to learn very complex and non-linear image filters [9].

Image analogies has been largely used in many applications such as texture synthesis [2], curves synthesis [10], super resolution [8], image colorization, image enhancement and artistic filters [14], [15]. This new technique has been also used

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in supervised medical image segmentation [11] consisting in finding by analogies the same colored regions in medical images as those processed by the expert.

Recent work has been published and concerns contour detection by image analogies which attempts to locate contours as humans do [12]. A set of training images (artificial patterns) are proposed, producing several images of contours, at varying intensity levels. Each one is obtained applying the corresponding pattern (see figures in Table 1).

We present in this paper what can be achieved with these contours for outlines of objects detection. We note that the motion of these contours from one pattern to another is implicitly related to regions boundaries, similar to those required for segmentation. A fast motion is present when the considered part of image does not contain objects or regions. However, this motion is slow and the contours are sometimes static around regions boundaries. We prove theoretically this property in this paper and it serves as the basis for a new approach to outlines of objects detection. In section 2 we present a review of the contour detection by image analogy [12]. We propose in section 3 a theoretical foundation of our method. Section 4 is devoted to the experiments conducted on different images.

Table 1. Illustrative contours located using a selection (four) of the 14 artificial patterns. Note the increase of intensity around the located contours from left to right.

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2 Contour Detection Using Images Analogies: A Review [12]

The problem addressed in [12] is how to do for automatic location of contours on the query image I_B giving the result S_B in the same way as this is done for (I_A, S_A) where I_A is an initial image whose contours are manually located giving the synthesized image noted S_A (see figure 1).

Using the Image Analogy technique, each pixel q of I_B is classified (contour pixel or not) using the knowledge inferred from (I_A, S_A). The best match p^* of q is searched in I_A using the neighbourhoods $N(p)$, $N(q)$ of p and q. For this, p^* must verify the minimal value of the similarity measure $S_m(q, p)$ between $N(p)$, $N(q)$ pixels. A kernel $K(m \times m)$ is used in this measure in order to give high weight for pixels of four main directions (horizontal, vertical and two diagonals).

The main result is that if the training pair of images (I_A, S_A) and the query one I_B are taken from the same scene, the location of contour pixels of I_B is

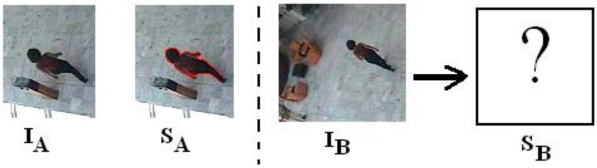


Fig. 1. Contour detection by analogy: the basic principle

done with success. However when I_B is from a different scene, the location of contour pixels cannot be done without the loss of many candidates. To locate all contour pixels, a set of constraints must be verified in the neighbours $N(p)$, $N(q)$. To avoid this, a set of pairs of artificial patterns (I_A, S_A) are proposed instead of hand drawn contours. The pattern I_A is composed by a shape with intensity F_A (Foreground) and a background with intensity G_A. The pattern S_A is the same as I_A, in addition, the contour is highlighted. The values of (G_A, F_A) are chosen so as for any query pixel q, the values of (G_B, F_B) representing the average of intensities of $N(q)$ regions verify the required constraints. The set of patterns $P_1, P_2, ..., P_{14}$ (see figure 2) are characterised by the values of G_A, F_A (background and foreground intensities):
$(0, 32)$, $(0, 64)$, $(0, 96)$, $(0, 128)$, $(0, 160)$, $(0, 192)$, $(0, 224)$, $(64, 192)$, $(64, 224)$, $(96, 224)$, $(128, 224)$, $(160, 224)$, $(192, 224)$, $(208, 240)$.

For each pattern (I_A, S_A) and for a query image I_B, only a set of contour pixels q will be localized such as the intensities of the neighbouring pixels in $N(q)$ verify a defined constraint related to (I_A, S_A) . We obtain then 14 images of contours corresponding to the 14 patterns (see figures in table 1).

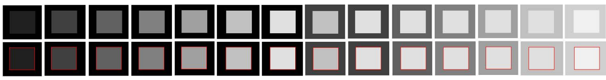


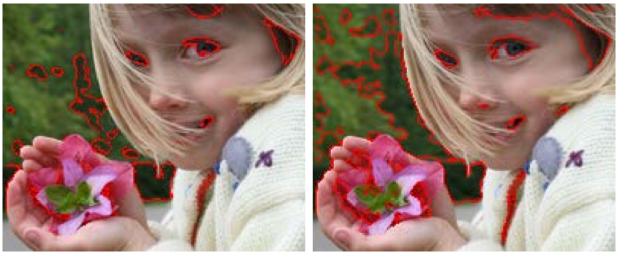
Fig. 2. Artificial patterns (I_A, S_A)

3 Outlines of Objects Detection

The use of artificial patterns allows locating contours of any query image I_B and provides the images: $S_{B,1}, ..., S_{B,n}$ where n is the number of artificial patterns $(n = 14)$. The computed contours are different from $S_{B,i}$ to $S_{B,i+1}$. Figures of table 2 illustrate the contours computed using the patterns P_3 and P_4. We note that inside of regions, contours are moving quickly from one pattern to another, and around region boundaries they are moving slowly or are steady.

First, we introduce the property of object boundaries, we prove it theoretically in the next. Finally, we describe our method for outlines of object detection based on this property.

Table 2. Contours located using the patterns P_3 and P_4



Property of Region's Boundary. *Contours extracted by image analogy are more stable at regions boundaries and are unstable for others parts of image.*

Proof.

We prove that if the contour is moving slowly, this implies that there is boundary defined as a gradual changing of intensity between neighbouring pixels. Let q be a contour pixel detected by the pattern P_i but not detected by the next one P_{i+1}, q' a contour pixel detected by the pattern P_{i+1} but not detected by the previous pattern P_i. Let G_{A^i}, F_{A^i} be the intensities of the two regions (background and foreground) of the pattern P_i.

If q is detected by the pattern P_i then the values G_B , F_B associated to $N(q)$ verify (see figure 3) [12]: $F_B \geq G_{B^i} + \delta l$ and $G_{A^i} < G_B \leq G_{B^i}$, where $G_{B^i} = (F_{A^i} + G_{A^i})/2$ and δl is the minimum intensity between two different regions.

As P_i and P_{i+1} are successive patterns, this means that whether $((F_{A^i} = F_{A^{i+1}})$ and $(G_{A^{i+1}} = G_{A^i} + 2\delta l))$ or $((G_{A^i} = G_{A^{i+1}})$ and $(F_{A^{i+1}} = F_{A^i} - (2\delta l)))$. We consider in this proof that $(G_{A^i} = G_{A^{i+1}})$, the same reasoning is also valid for other cases. If q is not detected using the pattern P_{i+1}, then F_B is necessarily lower than $G_B^{i+1} + \delta l$ where $G_{B^{i+1}} = (G_{A^{i+1}} + F_{A^{i+1}})/2)$, otherwise it will be detected by the pattern P_{i+1}. The belonging interval of F_B is then: $[G_{B^i} + \delta l, G_{B^{i+1}} + \delta l]$ (see figure 3). We assume that q is located as a contour pixel using the pattern P_i, and let q' be the neighbouring to p where G'_B, F'_B are the averages of intensities associated to $N(q')$. Now if we assume that q' is located by the pattern P_{i+1} and not detected by the pattern P_i, this means that the contour is steady (or moving slowly). We get from the previous result: $G_{B^i} + \delta l < F_B < G_{B^i} + 2\delta l$ and $G_{B^{i+1}} + \delta l < F'_B$. This is possible if $F'_B \geq G_{B^i} + 2\delta l$ and $G_{B^{i+1}} > G'_B > G_{B,i}$.

Let $dist = 1$ be the distance between the two pixels q and q' (see figure 4). Without loss of generality, we can write: $G'_B = (5 \times F_B + 5 \times G_B)/10$ and $F'_B = (10 * F_B + 5 * F''_B)/15$ such as F''_B is the average intensity of neighboring pixels to $N(q)$ and $m = 5$ is the size of the neighborhoods $N(p), N(q)$.

As $F'_B \geq G_{B^i} + 2\delta l$ and $G'_B < G_{B^{i+1}}$. The analysis of these relations gives the condition : $F''_B > 3G_{B^i} - 2F_{B^i} + 6\delta l$. However, as $F_B < G_{B^{i+1}} + \delta l$, $N(q')$ must then verify: $F''_B > G_{B^{i+1}} + \delta l$. Also, as $G'_B = (F_B + G_B)/2$, and $G_{B^{i+1}} + \delta l \geq F_B \geq G_{B^{i+1}}$, then $G_{B^i} \leq G_B < G_{B^{i+1}}$. Then, to locate q' as a contour pixel, a minimal difference of luminance intensity between F_B and F''_B in $N(q')$ equal to δl

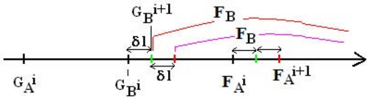


Fig. 3. Possible values of F_B in case where q is detected using only by one pattern

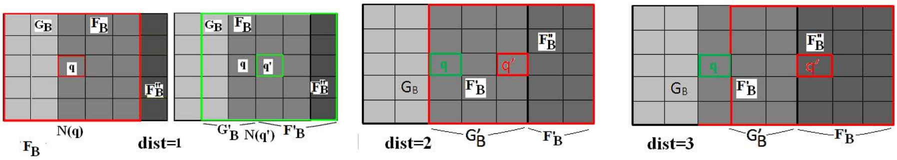


Fig. 4. Example of contour motion with $dist = 1, 2, 3$, $N(q)$, $N(q')$ are illustrated in red and green colors

must be verified. We note also the presence of a graduate changing of luminance intensities between G_B, G'_B, F'_B and F''_B. For the case $dist = 2$ and applying the same reasoning (see figure 4), we obtain: $G'_B = F_B$ and $F'_B = (5F_B+10F''_B)/15$. As $F'_B \geq G_{B^i}+2\delta l$ and $G_{B^{i+1}} > G'_B > G^i_B$, we get : $(2F''_B+F_B)/3 \geq G_{B^i}+2\delta l$. This implies that: $2F''_B \geq 3G_{B^i} + 6\delta l - F_B$, we get : $F''_B \geq G_{B^{i+1}} + \delta l$ thus: $F''_B \geq G'_B+\delta l$. When $dist = 3$ (see figure 4), we have: $G'_B = F_B$ and $F'_B = F''_B$. As $F'_B \geq G_{B^i} + 2\delta l$, we get the same relation: $F''_B \geq G'_B + \delta l$. Otherwise, if q' isn't detected by the pattern P_{i+1}, this means that there is no intensity variation in the neighbourhood of q.

3.1 Outline of Objects Detection: The Algorithm

We define the *energy* of contour as the number of times it is located using successive patterns with slow motion. We proved in previous subsection that when a contour is moving slowly and then with high energy, this means that it corresponds to object outline (border).

4 Results

We present in this section results obtained by applying our method to real images of BSD [4]. Firstly, we illustrate in table 3 the evolution of the contour located using artificial patterns. We can see that the located contour using P_7, P_8, P_9 is steady around object boundary except the central left part where the contour is moving fast (3 pixels from one pattern to another). For the patterns P_{10}, P_{11}, P_{12}, contours are moving fast from one pattern to other due to the absence of object boundary.

We applied our method using different values of energy defined as the number of times where the contours is steady or with slow motion. The increasing of energy value allows producing most significant contours corresponding to high

Algorithm 1. Object Outlines Detection

Extract Contours C_j^i using all patterns P_i
for Each successive patterns P_i, P_{i+1} **do**
  for Each contour C_j^i **do**
    Find the contour C_k^{i+1} neighbouring to C_j^i with $(dist < 3)$, $energy(C_k^{i+1}) + +$
  end for
end for
Select contours of given energy

Table 3. Contour's evolution using the patterns $P_7, P_8, P_9, P_{10}, P_{11}$

difference of intensities of related regions. Figures of table 4 illustrate the results obtained for energy equal to 3 and 4.

To measure the quality of outlines located, we used the ratios - precision, recall computed using the numbers of pixels found in the automatic contours vs the correct (hand-drawn) ones. For the data set BSD500 [4], for each image, five hand drawn contours are available as ground truth.

Depending of the used energy, which is synonymous to resolution level, the Precision and Recall have different values. More the energy increases, more precision increases because only the pixels contours corresponding to high difference of intensity are located and then the number of false candidates decreases. However, the recall decreases because the number of located outline pixels decreases. Figure 5 illustrates the values of Precision/Recall for Energy=1. These results

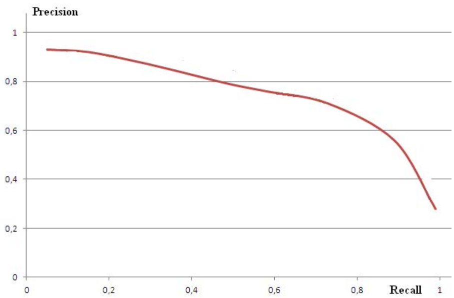
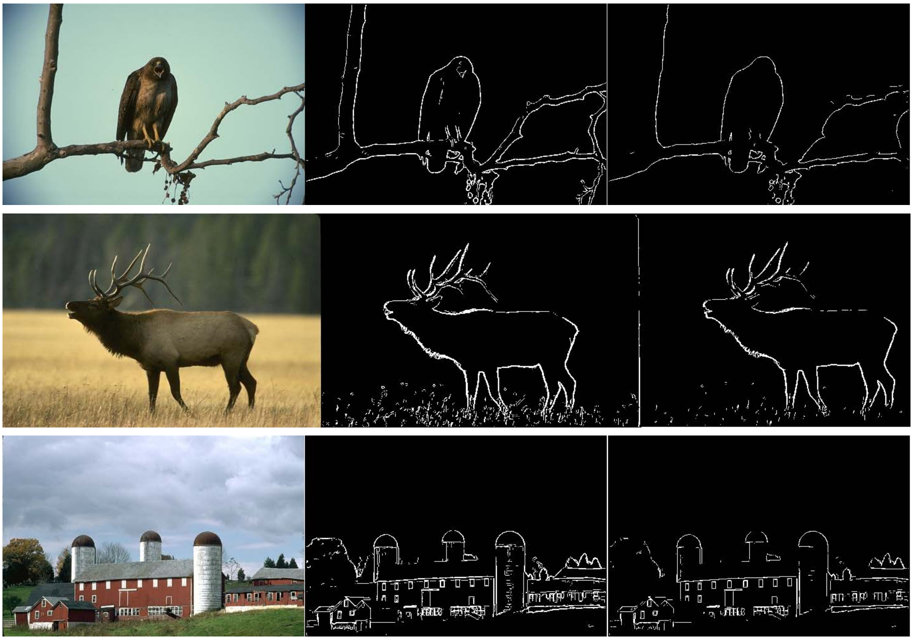


Fig. 5. Precision-Recall values for BSD dataset when Energy=1

Table 4. (*Left to right*): original image, located outlines with energy equal to 3 and 4



are similar to those of Arbelaez et al [4]. For high Recall values, our Precision is better and the difference reaches 20%. However for low Recall values, our Precision values are near from the values of Arbelaez et al [4], the difference is around 3%.

5 Conclusion and Future Work

We proposed in this paper a new technique for Object Outlines Detection based on image analogy. In the first part, we presented a review of contour detection by image analogy technique and then we gave a theoretical explanation of the steady contour motion corresponding to boundary object. The proposed algorithm has been applied to Weizmann and BSD datasets and the obtained results are presented. The obtained results are promising knowing that only intensity is used for this approach. We plan to add new attributes in the stage of contour detection e.g. color in order to locate the contours which may be missing using the current approach.

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