# STRAIGHT SUBJECTIVE CONTOUR DETECTOR

*Boshra Rajaei*[2,1], *Rafael Grompone von Gioi*[1], *Gabriele Facciolo*[1], *Jean-Michel Morel*[1]

[1] CMLA, ENS Cachan, France
[2] Sadjad University of Technology, Mashhad, Iran

## ABSTRACT

Subjective contours or illusory contours are an important aspect of human perception. These are perceptual image edges in which the stimulus does not present the usual high gradient of normal edges. Along subjective contours, image contrast is very weak or completely missing, so that no local edge detector can recover them. For this reason such contours are called subjective or even illusory. Their perception is induced by the presence of small pieces of edges and of tips of other long edges incident on the contour, thus suggesting the presence of an occluding object with fading contrast with respect to the background. Indeed, in real-world images, edge information of foreground objects is often partly missing due to poor contrast of the object with respect to its background. Nevertheless, the object's contour is still perceived by the presence of object's or background's detail that end up abruptly along the contour. In this paper, we handle the detection of straight subjective contours (SSC), using an *a contrario* approach to control the false detection rate. The algorithm exploits the tips of line segments produced by the well-known parameterless LSD method. The subjective straight contours are obtained by grouping free tips of parallel line sets, together with aligned short edge pieces. This detection is fully automatic and is demonstrated on a set of images containing subjective contours.

***Index Terms***— subjective contours, a contrario, number of false alarms, line segments, LSD.

## 1. INTRODUCTION

Subjective contours are perceived occlusion edges in the absence of luminance edges. The ability of human beings to recognize objects by completing object boundaries has been investigated in many psychophysical studies [1, 2, 3, 4, 5]. Kanizsa and his collaborators designed figures that induce subjective contours. Figure 1 shows two Kanizsa-like example images, where the illusory (*amodal*) contours of a triangle and a square can be perceived [6]. The perceived presence of edges on the white part of the contour of these polygons is of course not corroborated by any standard edge detector.

...

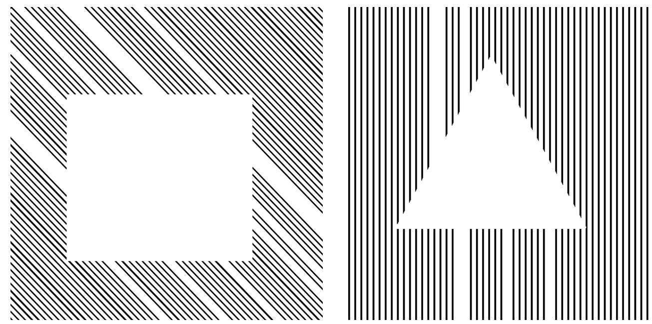

**Fig. 1**. Two Kanizsa-like examples of subjective contours. The sides of the illusory square and triangle have no contrast. For most observers it nevertheless creates a contour sensation called *amodal* or illusory contour.

Indeed, local edge detectors are based on local gradient magnitude and orientation.

In addition to natural illusions, state-of-the-art edge detectors often miss parts of edges. The state-of-the-art LSD algorithm [7], for example, follows a greedy approach to find meaningful line support regions with a common gradient direction. In presence of low contrast edges or noise, this greedy algorithm may produce gaps in the detection. Short line segments may be also missing for not satisfy the meaningfulness test. Other well-known segment detectors like EDLines [8] suffer from the same drawbacks, especially in high-resolution images [9]. Figure 2 illustrates these undesirable effects on LSD outputs.

In the past few years, several extensions of the LSD algorithm have been introduced to detect more complex structures in images by grouping line segments. In [9] the authors suggest a multiscale extension of LSD to deal with the over-segmentation issue. Another work extends it to the detection of polygonal lines and elliptical arcs [10]. In [11] line segments are grouped by Gestalt rules [12] to detect higher level features in images such as good continuation, parallelism, and non-local alignment.

In this paper, we address the detection of *straight subjective contours* (SSC). Its main idea is to generate an SSC candidate by grouping aligned and well-distributed tips of parallel line segments. In the case of partially detected SSC there

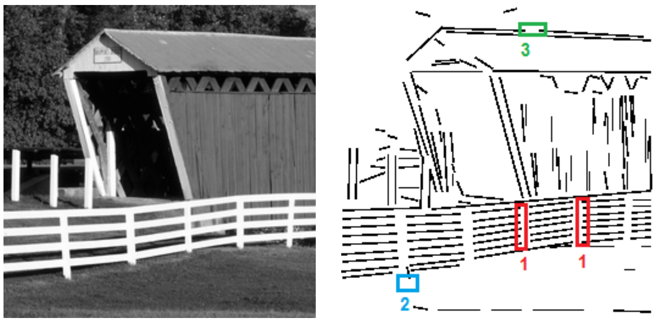


**Fig. 2**. Undesirable effects in results from the LSD algorithm (right) for a sample input image (left): (1) missed short segments (only one is detected in (2)), (3) gaps in an edge caused by a local perturbation.

may also be short segments along the same alignment that reinforce it. After iteratively detecting all distinct candidates, an *a contrario* approach is proposed to validate the presence of a SSC and eliminate false detections.

The rest of this paper is organized as follows: Section 2 introduces the theoretical formulation of the proposed *a contrario* model. In Section 3 the SSC detector algorithm is described in the form of three pseudocodes. Interesting detections of subjective contours from Kanizsa-like figures and some other real-world images are shown and commented in Section 4. Section 5 concludes the paper and explains our future research directions.

## 2. *A CONTRARIO* MODEL

In the *a contrario* framework [13], an event of interest $e$ (defined up to a certain precision) is called meaningful if its occurrence is non-accidental. This means that it could rarely happen just by chance. Thus we must first define the event, then evaluate its rarity in a random model, which needs be defined too. The stochastic expectation of $e$ is called its number of false alarms (NFA) and is defined as

$$\mathtt{NFA}(e) = N_{test} P_{H_0}(e) \tag{1}$$

where $N_{test}$ is the theoretical number of events $e$ to be tested and $P_{H_0}(e)$ is the probability of $e$ occurring under the stochastic model $H_0$ (to be defined). Using this equation, an event $e$ is called $\epsilon$-meaningful if and only if $\mathtt{NFA}(e) < \epsilon$.

Our subjective contour event is illustrated in Figure 3 and it is defined as follows.

**Definition 1.** *A straight subjective contour event $S$ is defined as a triplet $(R, \Sigma_1, \Sigma_2)$, where $R$ is a $w \times L$ rectangle divided into $c$ boxes of size $w \times l$, and $\Sigma_1$ and $\Sigma_2$ are two sets of line segments. The set $\Sigma_1$ contains $k_1$ parallel segments along direction $\theta_1$ (with tolerance $\Delta\theta$) and with one of their tips contained in the rectangle $R$. The set $\Sigma_2$ contains $k_2$ parallel segments with both tips contained in $R$ and orientation $\theta_2$ (with tolerance $\Delta\theta$), where $\theta_2$ is the orientation of $R$ main axis. The number of boxes $b$ occupied by at least one tip of a segment from $\Sigma_1$ gives a measure of the regularity along $R$ of the SSC.*

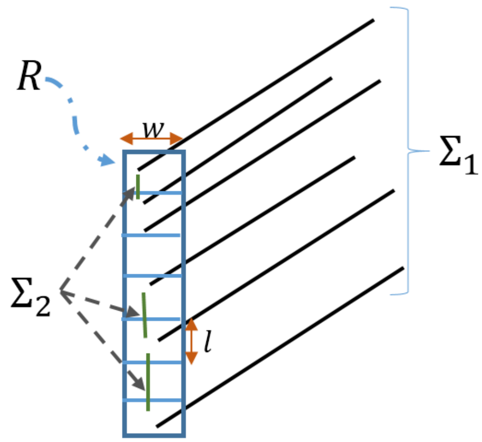


**Fig. 3**. A sample observation of $S$ event with $k_1 = 4$, $k_2 = 3$, $\theta_1 = 45°$, $\theta_2 = 90°$ and three out of five boxes are occupied with total seven tips. Note that the first and last $\Sigma_1$ line segments and their corresponding boxes are not taken into account in NFA calculations. Also, while counting total number of tips only one tip per line segment is considered.

Inspired by [14], the partitioning of the rectangle $R$ into $c$ boxes allows to evaluate the spatial distribution of the tips: if all the tips of $\Sigma_1$ are concentrated in a part of $R$, only some boxes would be occupied, characterizing an irregular distribution; inversely, most boxes would be occupied if the tips are well distributed along $R$.

The proposed *a contrario* model $H_0$ assumes $N$ stochastic line segments with independent orientation and a uniform distribution of tips on the image domain. The probability of the event $S$ in $H_0$ is given by

$$P_{H_0}(S) = \underbrace{\sum_{t=b}^{c} \frac{\binom{k_1-1}{t-1}\binom{c}{t}}{\binom{k_1+c-1}{k_1}}}_{\text{term 1}} . \underbrace{\mathbb{B}(n, k_1, p_1)}_{\text{term 2}} . \underbrace{\mathbb{B}(n, k_2, p_2)}_{\text{term 3}} . \tag{2}$$

The first term computes the probability that at least $b$ boxes are occupied by tips of $\Sigma_1$, out of a total of $c$ boxes in $R$. We define a histogram of segment directions $h$, where $h(d)$ denotes number of segments with orientation $d$ and the bins of the histogram have size $\Delta\theta$. Let us denote $p_1 = \frac{h(\theta_1)}{\sum_d h(d)}$ the probability of observing a line segment with orientation $\theta_1$ (up to a precision $\Delta\theta$) and accordingly $p_2 = \frac{h(\theta_2)}{\sum_d h(d)}$ for the orientation $\theta_2$. Then, the second term $\mathbb{B}(n, k_1, p_1)$ corresponds to the probability of observing "at least $k_1$ line segments along direction $\theta_1$ given that total of $n$ line segments have their tips randomly distributed inside $R$". Here,

$\mathbb{B}$ denotes the tail of binomial distribution. The last term $\mathbb{B}(n, k_2, p_2)$ corresponds to the orientations of the set $\Sigma_2$.

Every pair of parallel line segments (parallel up to a tolerance $\Delta\theta$) defines a distinct event $S$ for each given rectangle width $w$ and number of boxes $c$. Since we consider $W$ different widths for the rectangle $R$ and $C$ different numbers of boxes, the total number of tests is

$$N_{test} = W \cdot C \cdot \sum_{d} \binom{h(d)}{2}, \tag{3}$$

where the term $\binom{h(d)}{2}$ computes all the different ways of selecting two line segments with the same orientation within the tolerance $\Delta\theta$.

We now have all the elements to complete the *a contratio* formulation. Using equations 2 and 3, the NFA of the SSC event becomes

$$\texttt{NFA}(S) = N_{test} \cdot P_{H_0}(S). \tag{4}$$

Subjective contour events $S$ with $\texttt{NFA}(S) \leq \epsilon$ will be deemed meaningful and returned as the detected SSCs. Following [13] we set $\epsilon = 1$ which corresponds to accept on average one accidental detection in $H_0$ per image.

## 3. THE ALGORITHM

To apply the proposed *a contrario* model on an image, we first need to detect potential candidates for the $S$ event. Each candidate starts by considering any two tips belonging to parallel line segments along an arbitrary direction $\theta_1$ (up to a tolerance $\Delta\theta$). Then, a rectangle $R$ divided into boxes is mapped to the tips so that the tips locate in the middle of the first and last boxes. For each pair of tips the algorithm tests $W$ different rectangle widths and $C$ different number of boxes from which only the most meaningful event is preserved. The observation is completed by calculating $k_1$ as the number of line segments along $\theta_1$ with exactly one tip inside $R$ and $k_2$ as the number of line segments along $\theta_2$ with at least one tip inside $R$. The candidates are then evaluated using equation 4 and the events $S$ with smallest NFA (in a sense described below) are kept as detected straight subjective contours.

Algorithm 1 describes the overall steps for calculating SSCs. Algorithms 2 and 3 are pseudo-codes for the candidate search and validation process, respectively. Note that Algorithm 1 includes a crack removal step that aims at eliminating small gaps along LSD line segments due to partial gradient drop-outs. The crack removal step employs the non-local alignment (NLA) detector algorithm which is an *a contrario*-based approach as well and joins aligned LSD segments with close tips. We refer the interested reader to [11] for a detailed description of the method in addition to an online demo of the algorithm.

**Algorithm 1:** Straight subjective contour detector

**input :** $\mathcal{L}$ A list of size $n_s$ of line segments
$\Delta\theta$ orientation tolerance
**output:** $\mathcal{S}$ A list of SSCs

$\mathcal{L} = \texttt{crack\_removal}(\mathcal{L})$ *Using NLA detector algorithm [11].*

$h = \texttt{cal\_dir\_hist}(\mathcal{L})$ *Calculating direction histogram in degrees.*

$\mathcal{S}' \leftarrow \texttt{findCandidate}(\mathcal{L}, h, \Delta\theta)$ Algorithm 2 *Find all potential SSC candidates along with their NFA value*

$\mathcal{S}' = \texttt{sortCandidates}(\mathcal{S}')$ *Sort SSC candidates in an descending order of their NFA.*

$\mathbf{S} \leftarrow \texttt{findSSC}(\mathcal{S}')$ Algorithm 3 *Final SSC detection with the smallest NFA.*

## 4. EXPERIMENTAL RESULTS

We selected images from urban scenes, furniture and other man-made structures that provide many occlusions in the form of straight line geometries. Using Algorithm 1, the LSD line segments were first merged by the non-local alignment detector algorithm [11]. The NLA detector has two input parameters: $\theta$ and $\rho$, indicating the orientation tolerance (in degrees) between successive aligned line segments and the maximum distance (in pixels) between their tips, respectively. In the following experiments the $\theta$ and $\rho$ parameters were set to $10^\circ$ and 5 or 10 pixels (depending on input image resolution). These parameters were fixed in all experiments. The other piece of information necessary to Algorithm 1 is the parallelism tolerance $\Delta\theta$ that is set to $3^\circ$.

To control the complexity of Algorithm 2, we restrict our candidate search to $W = 8$ different rectangle widths, and $C = 8$ different regular partitions of the rectangle. Furthermore, we apply three other constraints ($5 \leq w \leq 10$, $w \leq l \leq 3w$ and $k_1 \geq k_2 - 2$) to prune the search space and prevent very narrow or very thick rectangles from being validated. These constraints restrict the definition of what we can properly call a straight alignment.

Figure 4 shows the detected contours for several real-world and artificial images. The initial LSD line segments are also displayed. Note that the algorithm correctly detected almost all interesting subjective contours. In Figure 5 the advantage of crack removal step is emphasized as well.

Eventually, Figure 6 shows two Kanizsa-like figures and the corresponding subjective contours. The subjective sides of the square and triangle have been well detected.

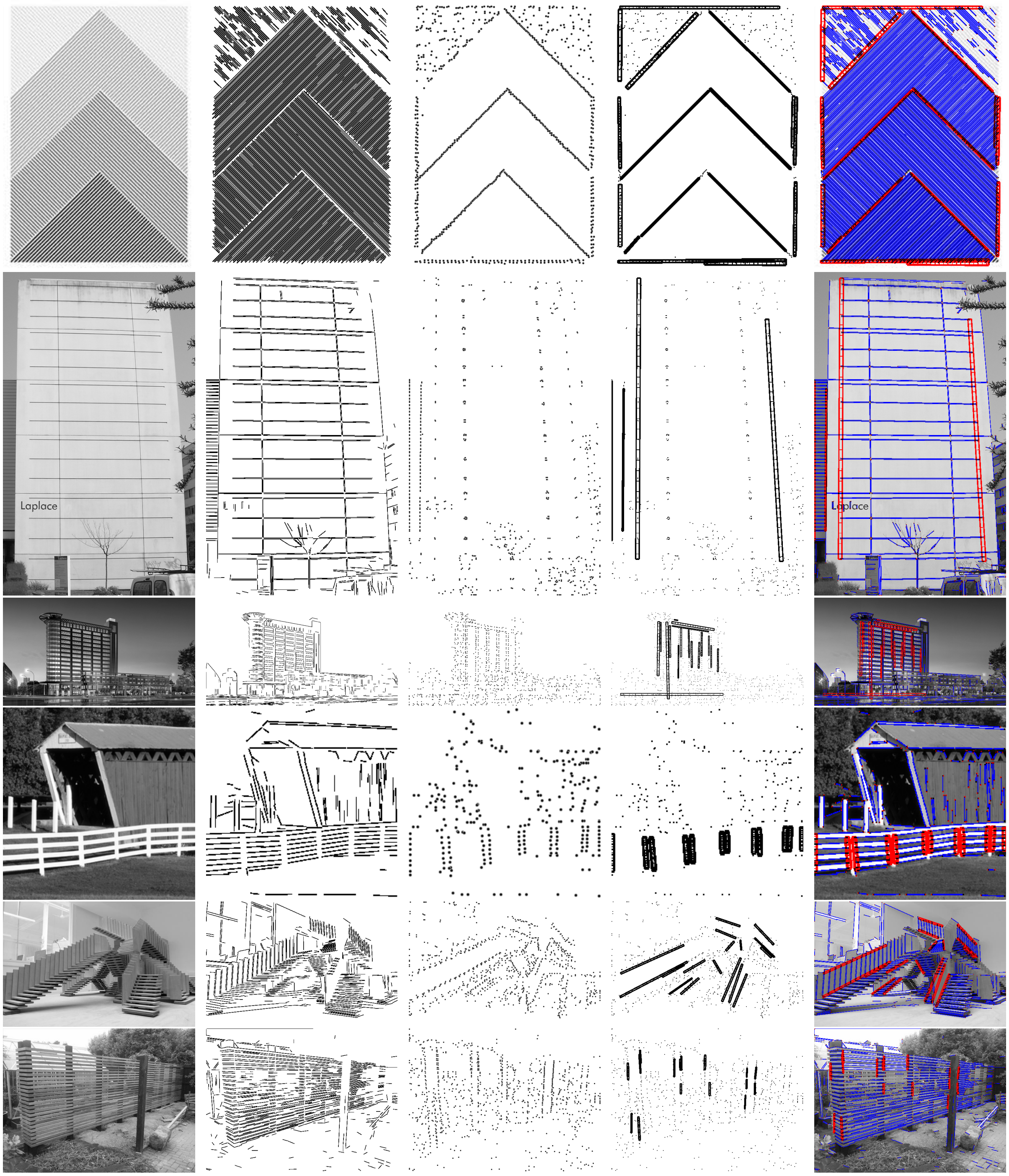


**Fig. 4**. Straight subjective contour detection results on (from top to bottom) parallel lines, Laplace, building, chalet and stairs figures. (From left to right) the original image, LSD line segments, LSD segment tips, straight subjective contours and a composite figure of original image with line segments in blue and subjective contours in red.

**Algorithm 2:** Find potential SSC candidates

**input** : $\mathcal{L}$ A list of size $n_s$ of line segments
$h$ histogram of segment directions (in degrees)
$\Delta\theta$ Orientation tolerance
**output:** $\mathcal{S}'$ A list of SSC candidates

$\mathcal{S}' \leftarrow \phi$
**forall** $(t, t')$ *tips from parallel* $(s, s')$ *segments* **do**
*distinct tips and segments*
  $\theta_1 \leftarrow mean(\angle s, \angle s')$
  $L \leftarrow distance(t, t')$
  $w \leftarrow \max(1, L/20)$
  **for** $i = 1$ **to** $W$ **do**
    $R = rect(t, t', w, L)$
    *A* $w \times L$ *rectangle is defined along the line connecting* $t$ *and* $t'$.
    $\theta_2 \leftarrow \angle R$
    $\Sigma_1 = search\_parallel(R, \theta_1)$
    *Find all segments along* $\theta_1$ *direction with exactly one tip inside* $R$.
    $k_1 \leftarrow |\Sigma_1|$
    **for** $j = 0$ **to** $C - 1$ **do**
      $c \leftarrow k_1 - j$
      Divide $R$ into $c$ equal partitions
      $\Sigma_2 = search\_oriented(R, \theta_2)$
      *Find all segments along* $\theta_2$ *direction with at least one tip inside* $R$.
      $k_2 \leftarrow |\Sigma_2|$
      $b = count\_occupied(R, c, \Sigma_1)$
      *The number of occupied partitions by* $\Sigma_1$ *segment tips.*
      Consider the candidate as $S$
      Compute $\mathtt{NFA}(S)$ using equation 4
      **if** $\mathit{NFA}(S) \leq \epsilon$ **then**
        $\mathcal{S}' \leftarrow \mathcal{S}' \cup \{S\}$
    $w \leftarrow w/\sqrt{2}$

**Algorithm 3:** Validate SSC candidates

**input** : $\mathcal{S}'$ A list of sorted SSC candidates
**output:** $\mathcal{S}$ A list of meaningful straight subjective contours

$valid(1..n_s) \leftarrow true$
**forall** $\{S\}$ *candidates in* $\mathcal{S}'$ **do**
  **if** $\mathit{NFA}(S) \leq \epsilon$ **then**
    **forall** *segment* $s$ *in* $S$ **do**
      **if** $!valid(s)$ **then**
        Skip the candidate
    $\mathcal{S} \leftarrow \mathcal{S} \cup \{S\}$
    **forall** *segment* $s$ *in* $S$ **do**
      $valid(s) \leftarrow false$

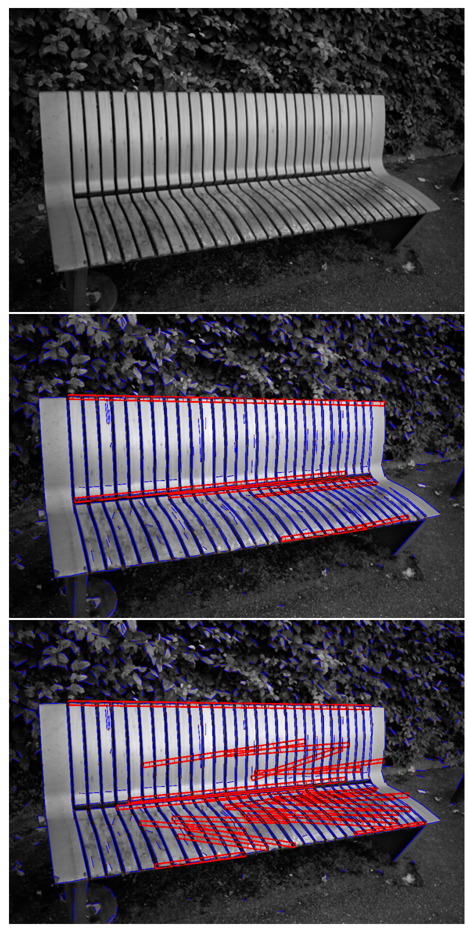

**Fig. 5**. The effect of the crack removal step on results of SSC detector algorithm. (From top to bottom) original chair image, subjective contours with and without crack removal step.

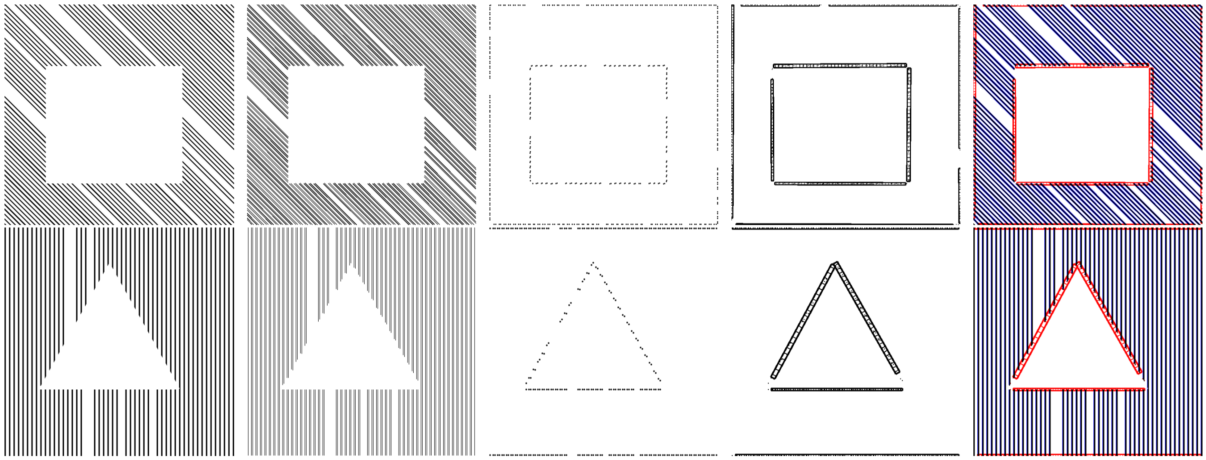

**Fig. 6**. Straight subjective contour detection results on Kanizsa-like square and triangle figures. (From left to right) the original image, LSD line segments, LSD line segment tips, straight subjective contours and a composite figure of original image with line segments in blue and subjective contours in red.

## 5. CONCLUSION

In this paper we proposed a fully automatic method for straight subjective contour detection in digital images. The algorithm is based on the common stochastic *a contrario* model and shows convincing results on real-world images. We notice that examining each candidate in the exhaustive search part (Algorithm 2) is inherently independent from the other searches. Therefore, the algorithm may be easily parallelized.

Our future research trends will be this acceleration, which will also make it possible to extend the process to general curved subjective contours.

## 6. ACKNOWLEDGMENT

## 7. REFERENCES


[1] M. K Albert, "Parallelism and the perception of illusory contours," *Perception*, vol. 22, no. 5, pp. 589–595, 1993.

[2] B. J Gillam, S. G Wardle, and E. Vecellio, "Orientation contrast and entropy contrast in the genesis of subjective contours along thin lines," *Perception*, vol. 43, no. 1, pp. 7–22, 2014.

[3] B. Gillam, "Perceptual grouping and subjective contours," in *The perception of illusory contours*, pp. 268–273. Springer, 1987.

[4] G. W Lesher, "Illusory contours: Toward a neurally based perceptual theory," *Psychonomic Bulletin & Review*, vol. 2, no. 3, pp. 279–321, 1995.

[5] R. van Lier and W. Gerbino, "Perceptual completions," *Oxford handbook of perceptual organization*, pp. 294–320, 2015.

[6] G. Kanizsa, "Subjective contours," *Scientific American*, vol. 234, no. 4, pp. 48–52, 1976.

[7] R.G. von Gioi, J. Jakubowicz, J.-M. Morel, and G. Randall, "LSD: A Fast Line Segment Detector with a False Detection Control," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 4, pp. 722–732, 2010.

[8] C. Akinlar and C. Topal, "Edlines: A real-time line segment detector with a false detection control," *Pattern Recognition Letters*, vol. 32, no. 13, pp. 1633–1642, 2011.

[9] Y. Salaün, R. Marlet, and P. Monasse, "Multiscale line segment detector for robust and accurate sfm," in *23rd International Conference on Pattern Recognition (ICPR)*, 2016, vol. 9.

[10] V. Pătrăucean, P. Gurdjos, and R.G. von Gioi, "Joint a contrario ellipse and line detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 4, pp. 788–802, 2017.

[11] B. Rajaei, R.G. von Gioi, and J.-M. Morel, "From line segments to more organized gestalts," in *IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)*, 2016, pp. 137–140.

[12] Johan Wagemans, James H Elder, Michael Kubovy, Stephen E Palmer, Mary A Peterson, Manish Singh, and Rüdiger von der Heydt, "A century of gestalt psychology in visual perception: I. perceptual grouping and

figure–ground organization.," *Psychological bulletin*, vol. 138, no. 6, pp. 1172, 2012.

[13] Agnès Desolneux, Lionel Moisan, and Jean-Michel M Morel, *From gestalt theory to image analysis: a probabilistic approach*, vol. 34, Springer, 2007.

[14] J. Lezama, J.-M. Morel, G. Randall, and R.G. Von Gioi, "A contrario 2d point alignment detection," *IEEE transactions on pattern analysis and machine intelligence*, vol. 37, no. 3, pp. 499–512, 2015.