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An improved model for surround suppression by steerable filters and multilevel inhibition with application to contour detection

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ABSTRACT

Psychophysical and neurophysiological evidence about the human visual system shows the existence of a mechanism, called surround suppression, which inhibits the response of an edge in the presence of other similar edges in the surroundings. A simple computational model of this phenomenon has been previously proposed by us, by introducing an inhibition term that is supposed to be high on texture and low on isolated edges. While such an approach leads to better discrimination between object contours and texture edges w.r.t. methods based on the sole gradient magnitude, it has two drawbacks: first, a phenomenon called self-inhibition occurs, so that the inhibition term is quite high on isolated contours too; previous attempts to overcome self-inhibition result in slow and inelegant algorithms. Second, an input parameter called "inhibition level" needs to be introduced, whose value is left to heuristics. The contribution of this paper is two-fold: on one hand, we propose a new model for the inhibition term, based on the theory of steerable filters, to reduce self-inhibition. On the other hand, we introduce a simple method to combine the binary edge maps obtained by different inhibition levels, so that the inhibition level is no longer specified by the user. The proposed approach is validated by a broad range of experimental results.

1. Introduction

Edge detection is an important problem in computer vision and pattern recognition, with many applications in both scientific and practical problems, such as object recognition or shape analysis. Some existing approaches are based on differential [1], statistical [2], and local phase [3,4] analysis, machine learning [5,6], active contours [7,8], perceptual organization [6], graph theory [9,10], and multiresolution analysis [11]. Despite of the huge amount of work that has been done in this area, there is still room for improvement of the existing algorithms and the development of new, more effective ones.

We make use of the insights obtained in psychophysics and neurophysiology of the visual system (of primates) in order to improve edge detection algorithms. Specifically, we consider a neural mechanism called *surround suppression* that is observed in areas V1 and V2 of the (monkey) brain.[1] Its essence is that the response of an orientation selective neuron to a local oriented stimulus is inhibited by the presence of other similar stimuli in the immediate surroundings. In previous work [12], we proposed a simple computational model for surround suppression. It is based on the computation of an inhibition term [12], which is defined as the local average of the gradient magnitude on a ring around each pixel. The inhibition term is supposed to be high on texture and low on isolated edges. When the inhibition term (multiplied by a scaling factor called *inhibition level*) is subtracted from the gradient magnitude, the resulting quantity discriminates between object contours and texture edges better than the sole gradient magnitude.

This approach has two drawbacks. First, neighboring parts and the same contour will inhibit each other to a certain extent. Previous attempts to overcome this problem, called self-inhibition, result in slow inelegant algorithms [13,14]. Second, the weight with which the inhibition term, called the inhibition level, needs to be multiplied is an input parameter that must be specified by the user and its optimal value may vary from image to image (Fig. 1).

In this paper, we overcome the aforementioned limitations in two ways: (i) we develop a new operator for the computation of the inhibition term, based on the theory of steerable filters, which avoids self-inhibition and is much faster than previous methods. (ii) We propose a simple algorithm which combines the binary edge maps obtained for different values of the inhibition level. In this way, the inhibition level needs no longer be specified by the user.

The rest of this paper is organized as follows: after a short review of previous work in edge detection (Section 2), we present the proposed edge detector (Section 3), demonstrate its effectiveness and advantages over the existing surround suppression

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[1] The areas V1 and V2 of the brain in mammals, also called primary visual cortex and pre-striate visual cortex, respectively, are the first two areas in the visual cortex in which low level visual stimuli are processed.

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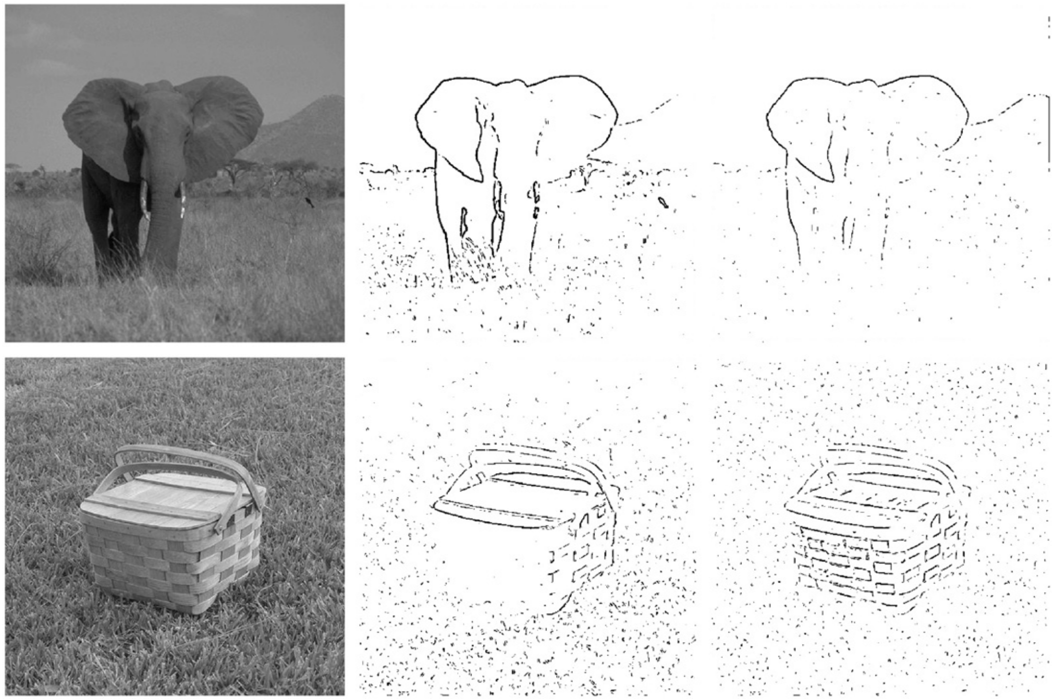

Fig. 1. From left to right: input image and output of the approach proposed in [12] with inhibition levels equal, respectively, to 1 and 3. For the first image, low inhibition levels give better results, while for the second image the best results are obtained for high inhibition levels.

algorithms (Section 4), and finally present a discussion and conclusions (Section 5).

2. Background on edge detection

We now present a brief overview of the state of the art in the field of edge detection. We divide the existing algorithms into non-contextual and contextual methods. In the former, edges are detected by only looking at a small neighborhood of each pixels, while in the latter the information on a larger context is considered too.

2.1. Non-contextual methods

The existing non-contextual methods are based on (i) differential and (ii) statistical analysis, (iii) local energy and phase congruency, and (iv) combination of the aforementioned features by means of machine learning techniques. In the following, we shall briefly discuss these typologies of algorithms

Differential methods: Edges, identified as discontinuities of the input luminance profile $I(x,y)$, can be detected as points of high gradient magnitude. Specifically, edges are defined as the local maxima of the gradient magnitude. These points are given by the zero crossings of the second derivative $I_{vv}(x,y)$ of $I(x,y)$ in the direction v of the gradient, for which the third derivative is negative. $I_{vv}(x,y)$ is often replaced by the Laplacian, which has a simpler analytical expression and, on low-curvature points, is a good approximation of $I_{vv}(x,y)$ [15]. Zero-crossings which do not satisfy the condition on the third derivative, known in the literature as *phantom edges* [16], are local minima of the gradient magnitude and do not correspond to edges.

As pointed out in [17], the computation of the derivatives of a digital image is an ill-posed problem. To regularize it, the input image must first be convolved with a low-pass pre-filtering. Canny proposed to optimize the template filter with respect to the following three criteria: good detection, good localization and low multiple responses [18]. It was found that the optimal filter for step edges is very close to the first derivatives of a Gaussian function. Discretized version of these criteria have been formulated in [19,20].

Statistical approaches: Differential methods are unable to detect boundaries defined by texture changes. To overcome this restriction, it has been proposed to analyze the local pattern on a neighborhood $\mathcal{N}(\mathbf{r})$ around each pixel $\mathbf{r}$ by means of statistical tools. The simplest technique consists in dividing $\mathcal{N}(\mathbf{r})$ into two equal parts along a given orientation and using a two-sample statistical test of independence to measure the dissimilarity between the two halves. High values of the dissimilarity indicate the presence of a region boundary. This analysis is repeated for several directions and the one which gives rise to the maximum dissimilarity is regarded as the local edge direction [2,21]. More recently, these ideas have been extended to color images [22] and integrated to texture models [5].

Other statistical approaches look at the local distribution of the gradient. The most common descriptive features are eigenvalues and eigenvectors of the local covariance matrix of the gradient [23,24], and local angular dispersion of the gradient [25,26]. In general, statistical approaches are more effective than differential methods in detecting color and texture transitions, but they are computationally more demanding.

Phase congruency and local energy: The human visual system responds strongly to points at which phase information is highly ordered [27]. In [3,4], a quantity called phase congruency is introduced, which is always between 0 and 1, being 1 on those points for which all Fourier components are in phase. Its local maxima correspond to salient visual events, such as step, peak and roof edges [4]. These maxima can be detected by analyzing a different quantity $L(t) \triangleq \sqrt{[(x \star f_e)(t)]^2 + [(x \star f_o)(t)]^2}$, called local energy. Here, $f_e(t)$ and $f_o(t)$ are a symmetric and an anti-symmetric low-pass or band-pass filter, such that $f_o(t)$ is the Hilbert transform of $f_e(t)$. Several pairs of functions $f_e(t)$ and $f_o(t)$, known in the