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NEUROCOMPUTING
Neurocomputing 69 (2006) 1297–1300
www.elsevier.com/locate/neucom

Optimal contour integration: When additive algorithms fail

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Available online 3 February 2006

Abstract

Contour integration is a fundamental computation during image segmentation. Psychophysical evidence shows that contour integration is performed with high precision in widely differing situations. Therefore, the brain requires a reliable algorithm for extracting contours from stimuli. While according to statistics, contour integration is optimal when using a multiplicative algorithm, realistic neural networks employ additive operations. Here we discuss potential drawbacks of additive models. In particular, additive models require a subtle balance of lateral and afferent input for reliable contour detection. Furthermore, they erroneously detect an element belonging to several jittered contours instead of a perfectly aligned and thus more salient contour.

Keywords: Visual system; Neural networks; Illusion; Association field

1. Introduction

The segregation of a visual scene into distinct objects involves the search for the boundaries of image patches. In reality, this search is made complicated by occlusions, noise, low contrast of the contour elements as compared to the background textures etc. During the past years, two classes of contour integration algorithms emerged, which claim to solve these problems: probabilistic models of contour creation and contour integration from computer vision [8,12], and neuronal models employing horizontal connections [3] which represent links between feature detectors for edges with similar orientations [4]. Probabilistic models are backed with a solid mathematical definition of contour ensembles, and are therefore optimal for a specific contour detection problem. Neuronal models are in close relationship to the neurophysiological properties of the brain.

The prominent difference between those model classes is the form of interaction between the (afferent) input provided by the stimulus itself, and the (lateral) input emerging from the interactions between spatially separated image features. In probabilistic models, these two sources of inputs are evidences which are coupled multiplicatively, while in neuronal models, the inputs are summed in the dendrites of the neurons within an orientation column. Unfortunately, the input summation has some potential major drawbacks, namely:

(1) If the afferent input dominates the lateral input, neurons representing edges of a contour show only a marginally higher activation than neurons representing background edges, thus complicating contour detection.
(2) If, however, the lateral input dominates the afferent input, silent neurons can become active. These neurons can participate in forming ‘illusionary’ contours which may show only a marginally lower activation than neurons representing the actual contour to be detected.
(3) In order to avoid the two previous traps, each stimulus situation requires a well-balanced afferent and lateral input. The exact amount of balance, however, changes in every stimulus situation.

The listed problems are avoided if afferent and lateral contributions are combined multiplicatively. Because the visual system is very fast and efficient in contour detection tasks [5], the question arises whether the brain also employs multiplicative instead of additive interactions [2].

However, purely multiplicative models have other drawbacks when considering contours of different lengths. For

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0925-2312/$ - see front matter
doi:10.1016/j.neucom.2005.12.095

example, the algorithm proposed in Ref. [12] requires the contour to be closed. Otherwise the 'activity' in the model could completely drop to zero. Even though the biophysical mechanisms underlying a nearly multiplicative interaction are still not understood, there is voluminous experimental evidence for such nonlinear interactions, [6,7,9,1].

In the next section, we will present the model and demonstrate the implications of additive interactions on contour integration. We then finally discuss the consequences of our results for contour detection in the brain.

2. Theory and modeling

The model we consider is given by the differential equation

$$\tau\dot{A}(\mathbf{x},\theta) = -A(\mathbf{x},\theta) + g(I(\mathbf{x},\theta)), \tag{1}$$

where τ is a time constant, and $A(\mathbf{x},\theta)$ is the activity of a neuron (edge detector) with a receptive field centered at position $\mathbf{x}$ with orientation preference θ. The gain function is $g(I) = I$ for $I > 0$, and 0 otherwise. The synaptic input I is defined as $I = I_a I_{\mathrm{aff}} + I_l I_{\mathrm{lat}}$, where $I_{\mathrm{aff}}(\mathbf{x},\theta)$ denotes the afferent input to a neuron, and $I_{\mathrm{lat}}(\mathbf{x},\theta)$ is the lateral input from horizontal interactions. I_a and I_l are the strengths of the afferent and lateral input, respectively.

Typical contour ensembles can be characterized by conditional probability densities $\rho(\mathbf{x},\phi|\mathbf{x}',\phi')$ [8]. ρ describes the probability that a contour passing through $\mathbf{x}'$ in direction ϕ' will next pass through $\mathbf{x}$ in direction ϕ. For detecting contours, the brain could use this knowledge about contour statistics by adapting an appropriate interaction term W (association field), e.g. between neighboring orientation columns. Therefore, we define the lateral interactions as $W(\mathbf{x},\theta,\mathbf{x}',\theta') = \rho(\mathbf{x},\theta|\mathbf{x}',\theta')$, thus $I_{\mathrm{lat}} = \int WA\,\mathrm{d}\mathbf{x}'\,\mathrm{d}\theta'$.

For our simulations, we discretize Eq. (1) into $i = 1,\ldots,n_{\mathrm{pos}}$ hypercolumns comprising $j = 1,\ldots,n_{\mathrm{ori}}$ orientation columns each. In case of runaway excitation, we prevent the activity of becoming infinite by normalizing $\sum_{i,j} A(\mathbf{x}_i,\theta_j) = 1$ during integration. For estimating the saliency of an edge we can either sum the activities after convergence to a steady state $A_0 = A(t \to \infty)$, $s_{\mathrm{sum}}(\mathbf{x}_i) = \sum_j A_0(\mathbf{x}_i,\theta_j)$, or we can simply pick the maximum activation from one orientation hypercolumn $s_{\max}(\mathbf{x}_i) = \max_j A_0(\mathbf{x}_i,\theta_j)$. In order to reproduce results from psychophysical experiments [11] this saliency should increase with the extent to which an edge can be regarded as belonging to a contour, and with the length of that contour.

3. Simulations and results

We will demonstrate potential problems of the additive contour integration model (1) by constructing an ambiguous stimulus for a very simple simulation. We choose $n_{\mathrm{ori}} = 8$ directions with $I_{\mathrm{aff}}(\mathbf{x},\theta) = 1$ for $\theta = \phi(\mathbf{x})$, and 0 otherwise. Similarly, the coupling W is 50 for those nearest neighbors which are perfectly aligned to a straight contour, and 0 otherwise. We choose a 4×4 stimulus as depicted in Fig. 1, with a contour 1 of length $L_1 = 3$ and a contour 2 with $L_2 = 2$ elements. Now, we arrange the background edges such that only *one* background edge points towards a contour element of contour 1, but *six* background edges point towards the lower edge i of the shorter contour 2. A simulation with $I_a = I_l = 1$ shows that the summation estimator s_{sum} reports element i as nearly twice as salient as every other edge. This happens even though contour 1 contains more contour elements and should therefore be more salient than contour 2. In contrast, the maximum estimator displays the behavior which we expect from a good contour integration model: the three elements of contour 1 are most salient.

However, in the visual cortex not only neurons representing perfectly aligned, collinear elements are interconnected. Thus we investigate how the relative saliences of the two contours change if we apply a wider association field. For simplicity we assume a coupling of $W = 50$ for collinear neighboring edges, $W = 25$ if the target element's alignment deviates by 45°, and $W = 0$ otherwise. Again element i has the highest saliency s_{sum}. However, because of the wider association field the neuron corresponding to position and orientation of element i of contour two now gets lateral input from *five* neighbors. Therefore it is also most salient for the maximum estimator. We can interpret this situation as a superposition of several jittered contours passing through the same edge i, and hence making i more salient than the elements of one perfectly aligned, straight contour.

Now, we investigate how the saliency depends on the relation I_l/I_a with a less ambiguous stimulus depicted in Fig. 2(a) and the narrow association field. The model clearly detects the contour for $I_a = I_l$ as illustrated in

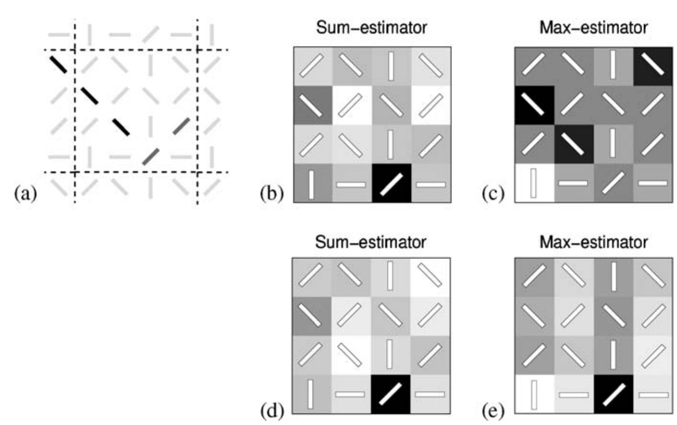

Fig. 1. (a) The dotted square contains a stimulus of 4×4 edges with periodic boundary conditions. It contains a long contour (black) and many shorter contours. One short contour is highlighted (dark grey), because many background edges (distractors) point towards it. On the right, saliencies of each edge as computed with the summation estimator (b) and the maximum estimator (c) for a narrow association field and (d) + (e) for a broader association field, respectively. On the square's gray scale, white corresponds to minimum, and dark to maximum saliency.

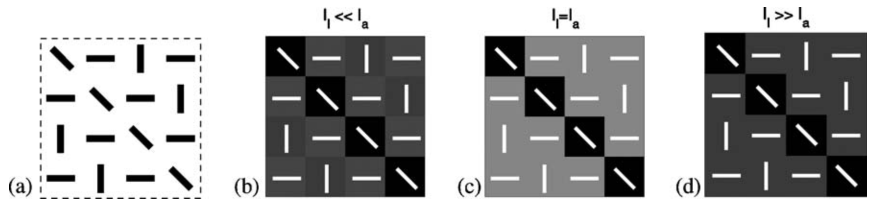

Fig. 2. (a) Stimulus with periodic boundary conditions, containing one contour on a very regular background. (b)–(d) Saliencies s_{sum} in each orientation hypercolumn for various values of I_l. Here the gray scale ranges from zero (white) to the maximum activity (black).

Fig. 2(c). However, with increasing I_l, the difference between the saliences of contour and background elements decreases, such that even small noise makes it impossible to detect the contour (Fig. 2(d)). The same is the case for increasing I_a. Here, the saliency approaches the afferent input, which is identical for each edge (Fig. 2(b)).

We further investigated a one-dimensional stimulus with periodic boundary conditions in an extended model with more realistic input functions and couplings [10]. Specifically, we simulated hypercolumns with $n_{ori} = 24$ possible directions, and used von Mises functions for the afferent input and lateral couplings. We choose a situation where a contour is difficult to detect: Among a background of clearly visible, but unaligned edges ($\sigma_{aff} = \pi/48$), a contour with blurred edge elements ($\sigma_{aff} = \pi/3$) is located. We determined the saliency s_{sum} of each edge and defined the separability index $S = (\langle s_c \rangle - \langle s_b \rangle)/(\langle s_c \rangle + \langle s_b \rangle)$ between the mean saliencies $\langle s_c \rangle$ and $\langle s_b \rangle$ of contour and distractor elements, respectively. The model detects the contour, as long as $S > 0$. The larger $|S|$, the more the model is robust to noise. Keeping I_l fixed, and varying I_a, we obtain a separability index $S \neq 0$ only around an optimal ratio of I_a/I_l. Even here, S is small, and Poisson noise applied on $g(I)$ in each iteration step averaged over $n = 1000$ neurons makes it impossible for the observer to distinguish between contour and background (see Fig. 3).

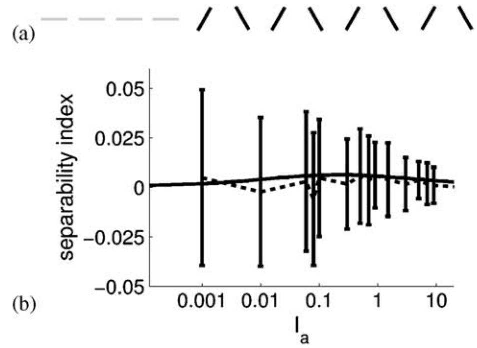

Fig. 3. (a) One-dimensional stimulus with periodic boundary conditions, consisting of four blurred contour elements (grey) and eight clearly visible background elements (black). (b) Separability index S for fixed I_l in dependence of I_a with (solid line) and without (dashed line) Poisson noise. S is averaged over 1000 trials. The error bars indicate the standard deviation.

4. Summary and outlook

Taken together, in the additive model a neuron with preferred orientation θ provides input to all its neighboring, aligned neurons with similar orientations even if these do not receive any afferent input as an evidence for an oriented edge in the stimulus at that location. This is a disadvantage for the summation estimator which takes all these inputs into account.

This difficulty is partially avoided by the maximum estimator s_{max}. However, this estimator predicts a high salience s_{max} for edges belonging to *several* short, jittered and therefore psychophysically little salient contours. These edges can be estimated to be much more salient than elements of a perfectly aligned, straight contour, which should be psychophysically more salient than every jittered contour. To test whether human perception of elements belonging to several contours is similar to the prediction of the model one could use psychophysical stimuli like the one depicted in Fig. 4. There a contour of nine Gabor patches with an orientation jitter of five degrees is in rivalry to an element j surrounded by six elements pointing towards the center of edge j.

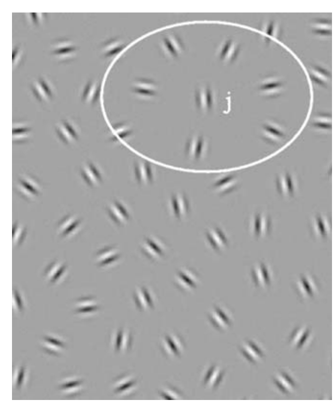

Fig. 4. Possible stimulus for psychophysical experiments that can reveal whether humans have similar illusions as predicted by the additive model. The white perimeter contains six edges pointing towards the edge j in the center. Below is a contour of nine elements with an orientation jitter of five degrees.

A second disadvantage of the additive model is that contour detection only works reliably in a limited range of I_a/I_l. For $I_a \gg I_l$, one can neglect the lateral input and the saliences $s \approx I_{aff}$ will reflect the afferent input only. For $I_l \gg I_a$, one almost looses the information about the actual stimulus orientation, and even with small noise, the maximum estimator should no longer be able to distinguish between two aligned and two perpendicular edges.

Despite multiplicative models seem to perform better in integrating contours [2], it is not known whether the brain makes use of this advantage: there are many situations in which human observers fail to detect contours. Thus, we are currently designing an experiment which will allow us to distinguish whether the brain's algorithm resembles more a multiplicative, or an additive strategy for contour integration.

Acknowledgement

This project has been supported by the Deutsche Forschungsgemeinschaft (DFG, SFB 517, author U.E.). We would like to thank Sunita Mandon and Andreas Kreiter for many fruitful discussions.

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