Negative fuse network

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The Negative Fuse Network

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Abstract

We describe the negative fuse, an analog model which encourages boundary completion in early vision regularization algorithms. This algorithm is an extension of the successful implementation of line processes in analog VLSI using the resistive fuse (Harris *et al.*) [1]. The negative fuse provides for true negative resistance regions for the enhancement of edges, making long connected edges more likely to occur. This model has a natural mapping into inexpensive, fast, low power analog hardware. We discuss the performance of a negative fuse element fabricated in VLSI and show simulations of network performance on digitized camera images.

1 Introduction

Standard regularization theory combines least squares methods with smoothness constraints, which leads to quadratic variational functionals with a unique, global minimum (Horn and Schunck [2]; Hildreth[3]; Poggio, Torre and Koch[4]; Poggio, Voorhees and Yuille, [5]; Grimson[6]). These quadratic functionals can be mapped onto linear resistive networks, such that the stationary voltage distribution, corresponding to the state of least power dissipation, is equivalent to the solution of the variational functional (Horn[7]; Poggio and Koch, [8]). Data is provided through the correct choice of data-dependent voltage sources and resistors at each node. Much research has gone into extending these quadratic variational functionals to allow for discontinuities. Geman and Geman[9] first introduced a class of stochastic algorithms, based on Markov random fields, that explicitly encode the absence or presence of discontinuities by means of binary variables. Their approach was extended and modified by numerous researchers to account for discontinuities in depth, texture, optical flow, and color. Various deterministic approximations, based on continuation methods or on mean field theory yield next-to-optimal solutions (Koch, Marroquin and Yuille[10]; Terzopoulos [11]; Blake and Zisserman[12]; Hutchinson *et al.*,[13]; Blake [14]; Geiger and Girosi[15]).

Considerable interest has focused recently on mapping vision algorithms onto analog or digital networks. Notably, Carver Mead[16] has been successful in developing subthreshold analog networks which implement various vision processes, such as an artificial retina chip (Mead and Mahowald)[17]. In this paper we first discuss the "resistive fuse", the first implementation of line process discontinuities in analog hardware. The resistive fuse was introduced by Harris[18][1] as a means of implementing discontinuities directly without the use of a hybrid analog-digital network to implement the smoothing function and the discontinuity detection independently. Section 3 describes the negative fuse, an idea that extends the resistive fuse concept to enhance boundary completion. This negative fuse effectively implements a two-threshold scheme where the intensity difference across adjacent pixels will be enhanced if discontinuities are present in the neighborhood of the pixels. We will study the hysteresis properties of this new network that encourages the smooth propagation of edges across gaps.

2 Resistive Fuse

Line discontinuties were first used by Geman and Geman as part of a Markov random field lattice to reconstruct surfaces from noisy images. Marroquin [19] applied this idea by using two coupled Markov Random fields (one for the depth values and the other for line processes) to solve the surface reconstruction problem. Koch, Marroquin and Yuille extended this further by using analog networks with discontinuities which vary continuously between 0 and 1. They also used a first-order model (membrane) to reconstruct the surface between sparse depth points of synthetic images.

Blake and Zisserman[12] used similar energy functions for first-order (membrane) and second-order (plate) networks to locate discontinuties in natural images. In forming the energy function for a weak membrane for the 2-D case, the sparse and noisy depth data $d_{i,j}$ are given on a discrete grid. Associated with each lattice point is the value of the recovered surface $u_{i,j}$ and two binary line discontinuities $h_{i,j}$ and $v_{i,j}$. Assuming that the surface is smooth except at isolated discontinuities, the functional to be minimized is given by

$$E(u,v,h) = \sum_{i,j}[(u_{i,j}-d_{i,j})^2+\lambda(u_{i,j}-u_{i,j+1})^2(1-v_{i,j})+\lambda(u_{i,j}-u_{i+1,j})^2(1-h_{i,j})+\alpha(h_{i,j}+v_{i,j})] \quad (1)$$

where λ and α are free parameters. The first term forces the surface u to be close to the measured data d. The second and third terms implement the piecewise smoothness constraint in the horizontal and vertical directions respectively. Horizontal and vertical line discontinuities are represented by $h_{i,j}$ and $v_{i,j}$. Fig 1 explains the choice of indices used for representing the line process variables. If all variables, with the exception of $u_{i,j}, u_{i+1,j}$, and $h_{i,j}$, are held fixed and $\lambda^2(u_{i+1,j}-u_{i,j})^2 < \alpha$, then it is "cheaper" to pay the price $\lambda^2(u_{i+1,j}-u_{i,j})^2$ and to set $h_{i,j}=0$ than to pay the larger price α. In other words. if the gradient becomes too steep, $h_{i,j}=1$, (i.e. a discontinuity is detected) and the surface is segmented at that location. Fig 1 explains the choice of indices used for representing the line process variables.

We use a deterministic approximation and map the functional E onto the circuit shown in Figure 2. The voltage at every gridpoint then corresponds to $u_{i,j}$. A voltage source is set to $d_{i,j}$ at every

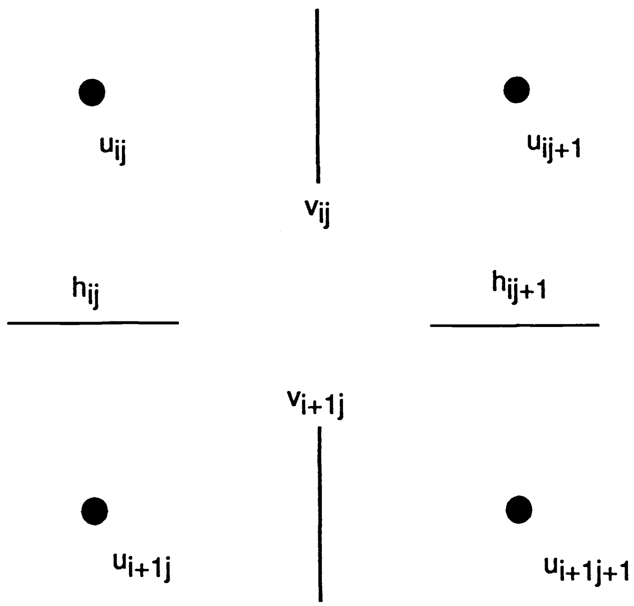

Figure 1: Description of indices

node. The conductance between the voltage source and the grid is assumed to be 1. In the absence of any discontinuities ($h_{i,j} = v_{i,j} = 0$), smoothness is implemented via a conductance of value λ^2 connecting neighboring grid points; that is, the nonlinear resistors in Figure 2a can simply be considered linear resistors. The cost functional E can then be interpreted as the power dissipated by the circuit. If parasitic capacitances are added to the circuit, E acts as a Lyapunov function of the system and the stationary voltage distribution corresponds to the smooth surface.

Harris[1] introduced a two-terminal nonlinear device called a resistive fuse to implement piecewise smoothness and discontinuities (Figure 2b). If the voltage drop across this device is less than $V_T = (\alpha^{1/2}/\lambda)$, the current through the device is proportional to the voltage, with a conductance of λ^2. This implements the smoothing function. If V_T is exceeded, the fuse breaks and the current goes to zero. Unlike the common electrical fuses in our houses, the operation of the resistive fuse is fully reversible. The I-V characteristic of this analog fuse is shown in Figure 2b. The linear part of the I-V curve produces a membrane-like smoothing function. This analog fuse implements a continuous version of the binary line discontinuities. There are some problems with using a weak membrane network. Even though the network possess hysteresis, this is insufficient to help propagate the edges towards forming complete boundaries. We attempt to improve the membrane energy by using a negative fuse.

3 The Negative Fuse

Conventional edge detectors assume that an edge is detected if the difference in intensity of a pixel from that of its neighbors exceed a pre-defined threshold. Such detectors have difficulty finding continuous edges and subsequent techniques like edge-linking are employed to fill in the gaps so

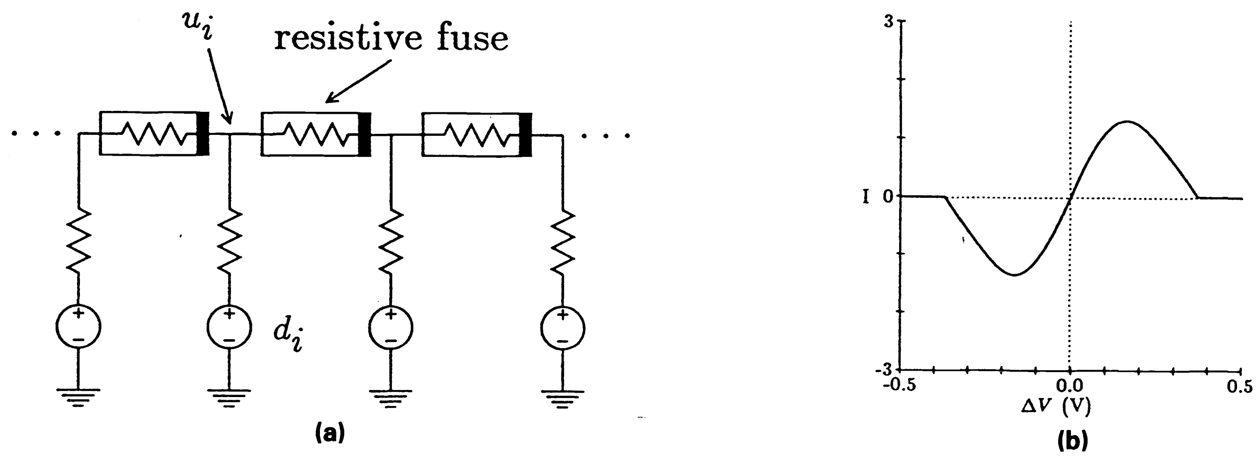

Figure 2: (a) nonlinear resistor network implementing line processes (b) measured IV curve of the resistive fuse (from Harris *et al.*)[1]

that closed contours are formed. Edge detectors like Canny's edge detector(Canny)[21] and mean field methods (Gieger and Girosi)[15] use two thresholds so that pixels with difference in intensities lying between the 2 thresholds have the potential of either being a discontinuity or not depending on whether discontinuities exist in their neighborhood.

In Geiger and Girosi's work on developing a mean field approximation as a good deterministic solution to MRF's problem, they pointed out that the gradient limit threshold of a weak membrane is sometimes insufficient to close a contour in the image. They proposed adding an extra penalty term to the membrane energy equation to increase the hysteresis effect. The extra penalty, corresponding to the following terms, is subtracted from the above energy, E.

$$P2 = \epsilon\alpha \sum_{i,j}(h_{i,j}h_{i,j-1}) + \epsilon\alpha \sum_{i,j}(v_{i,j}v_{i-1,j})$$

The first term in the equation above decreases the penalty paid for creating a horizontal discontinuity if one of the neighboring horizontal discontinuities is present. Similarly, a horizontal discontinuity created at a site will make the presence of neighboring horizontal discontinuities more likely. The second term decreases the penalty paid for creating a vertical discontinuity depending on the absence or presence of neighboring vertical discontinuities. These additional terms increase the amount of hysteresis in the network and encourages smooth propagation of edges to close gaps in contours. The variable ϵ can be varied continuously between 0 and 1. If $\epsilon = 0$, the total energy function reduces to that of the weak membrane. If $\epsilon = 1$, the penalty for creating a discontinuity will be reduced to zero and edges will appear everywhere.

In a very ad hoc fashion, Geiger and Girosi modified a similar energy function to the one above into a simpler form. Intuitively, the function of this new energy is to boost mediocre edges which lie between certain high and low threshold values. This boost may be enough to push neighboring edges over the threshold–cooperatively creating and extending contours which would not have been detected with a single threshold. This ad hoc energy form is mapped onto a circuit shown in Figure 2a and the the two-terminal nonlinear device has a current-voltage characteristic which is

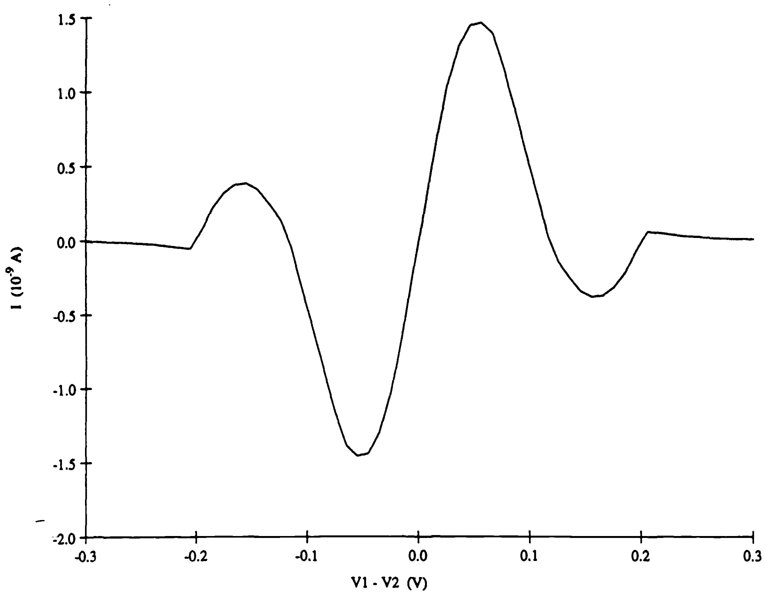

Figure 3: Measured current-voltage curve of an experimental analog VLSI negative fuse.

similar to the "derivative" of the energy (also known as "force"). We have implemented this new nonlinear device called the negative fuse because of the presence of a negative region below the x-axis in the current-voltage characteristic shown in Figure 3. The I-V characteristic of this negative fuse was measured from a fabricated analog VLSI device. The circuit for this device is based on the "bump" circuit which measures the similarity between analog voltages[22].

For the circuit in Figure 2a, the stationary voltage at every gridpoint corresponds to u_i. A voltage source is set to d_i at every node. In addition to this voltage source, there is a current source (not shown in the figure) which pumps current in or out of the node when the difference in the voltages of neighboring gridpoints fall within a certain range. This behavior is best explained by looking at the response of the negative fuse to various step heights.

If a large step is applied to a network of negative fuses and the voltage difference across a negative fuse exceeds a set upper threshold, there is essentially no smoothing across the nodes at the terminal of the fuse and the conductance of the fuse is zero. If the voltage difference is below a set lower threshold, the step is smoothed as in the weak membrane and the conductance is λ^2 If the voltage difference across the fuse falls between the set upper and lower thresholds, current is then pumped in or out of the corresponding nodes such that the voltage difference between these nodes is enhanced and the response of the negative fuse falls in the region where the conductance is now decreased till it reaches zero (see Figure 4). This enhanced voltage difference gives the step response its characteristic look of an overshoot on the upper edge and an undershoot on the lower edge.

In essence, the negative fuse helps the surface break along those nodes whose voltage difference is initially insufficient to cause the surface to break. However if the surrounding surface starts to break, this creates an "avalanche effect" which continues the breaking of the surface even along points with an insufficient voltage difference across them. This enhanced hysteresis property translates into further propagation of an edge to form complete boundaries.

In Figure 5, we show the influence of different values of ϵ on the current-voltage characteristic of

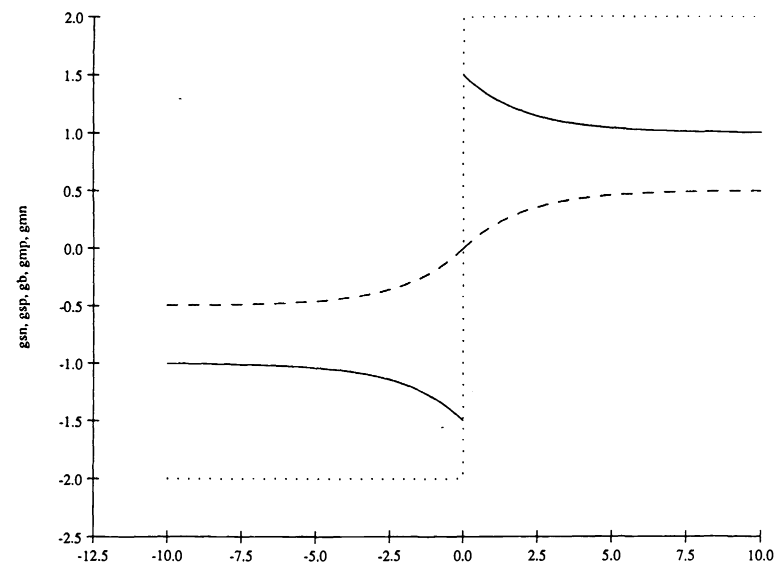

Figure 4: Step response of Negative fuse for different step heights.

the negative fuse. As the value of ϵ increases from 0, the influence of the neighboring discontinuities on the penalty function is correspondingly increased. This translates into an increasing negative region in the current-voltage characteristic of the negative fuse.

We have simulated a negative fuse network for smoothing and segmenting the Lena image shown in Figure 6a. The original 256x256 Lena image was smoothed and resampled on a pseudo-hexagonal grid. A hexagonal network of negative fuses were used to allow a richer set of edge neighborhood properties. We and others have observed that rectangular grids tend to over-emphasize horizontal and vertical edges. Figure 6b shows the segmented output and Figure 6c shows the extended continuous edges. These results demonstrate that the negative fuse network yields solutions with long, continuous edges. Honest comparisons between the negative fuse network and the standard weak membrane method are difficult. Certainly if all other parameters are held constant, the negative fuse network discovers more edges. The weak membrane technique could recover these same edges by lowering the edge threshold at the risk of signalling more "noise" edges or succumbing to the gradient limit on steep slopes.

4 Conclusion

We have demonstrated a modified version of the resistive fuse called the negative fuse which encourages boundary completion. The current-voltage characteristics of this fabricated analog VLSI device are analysed to show the capabilities of this element. This simulated network have been run on dense image data to show their segmentation and edge detection capabilities.

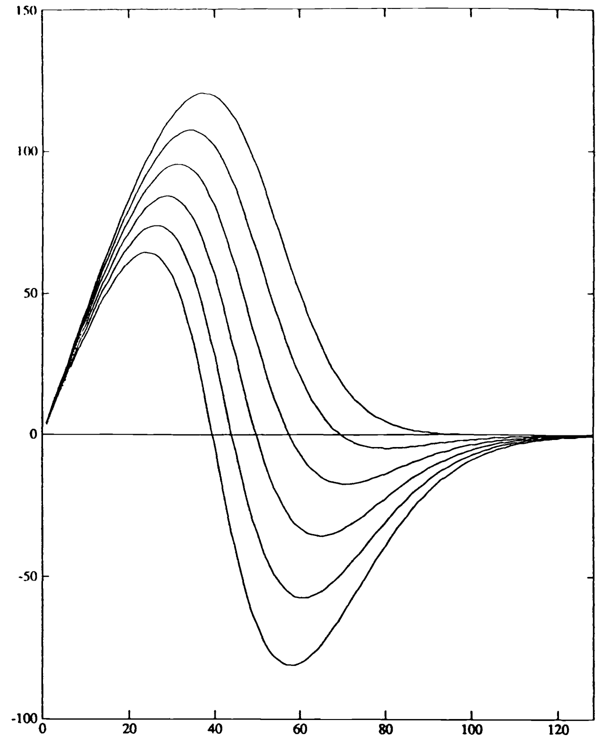

Figure 5: Measured IV curves for negative fuse for varying ϵ

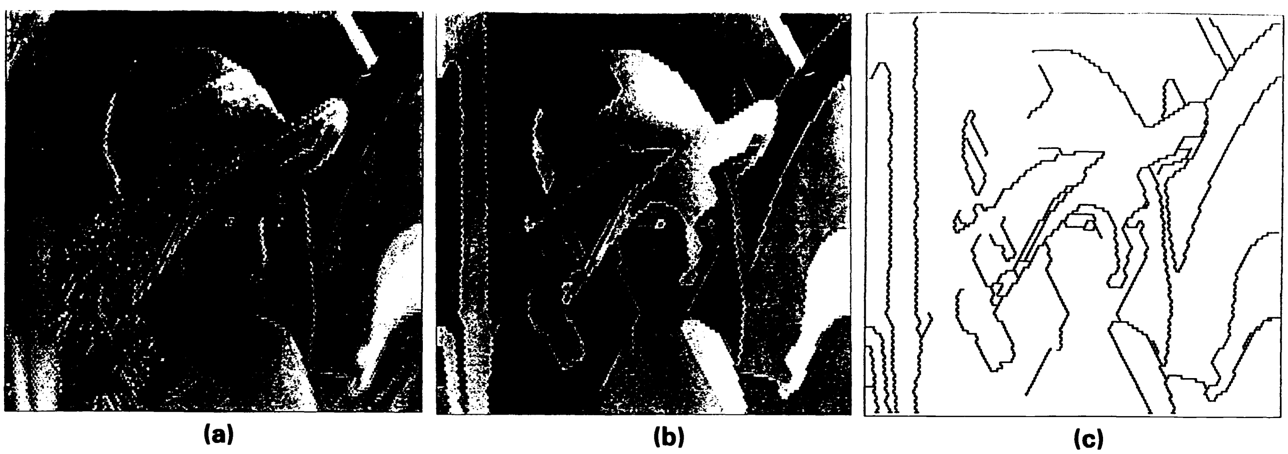

Figure 6: Negative fuse solution to Lena image. (a) shows the original Lena image (b) shows the final segmented image using the simulated network (c) shows the edges obtained after segmentation.

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