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Processing of Synthetic Aperture Radar Images by the Boundary Contour System and Feature Contour System

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ABSTRACT: An improved Boundary Contour System (BCS) and Feature Contour System (FCS) neural network model of preattentive vision is applied to two large images containing range data gathered by a synthetic aperture radar (SAR) sensor. The goal of processing is to make structures such as motor vehicles, roads, or buildings more salient and more interpretable to human observers than they are in the original imagery. Early processing by shunting center-surround networks compresses signal dynamic range and performs local contrast enhancement. Subsequent processing by filters sensitive to oriented contrast, including short-range competition and long-range cooperation, segments the image into regions. Finally, a diffusive filling-in operation within the segmented regions produces coherent visible structures. The combination of BCS and FCS helps to locate and enhance structure over regions of many pixels, without the resulting blur characteristic of approaches based on low spatial frequency filtering alone.

1. Introduction: Synthetic aperture radar sensors can produce range imagery of high spatial resolution under difficult weather conditions (Munson, O’Brien, and Jenkins, 1983; Munson and Visentin, 1989), but the nature of the image data affords some difficulties for interpretation by human observers. Among these difficulties is the large dynamic range of the sensor signal (five orders of magnitude), which requires some type of nonlinear compression merely to be represented and viewed. Among the other characteristics making interpretation difficult is inherent noise that results in a grainy appearance (speckle). To date, most approaches to automatic segmentation and to improving the appearance of SAR images for human interpretation have involved filtering or reconstruction using pixel-based statistical estimates of signal distributions for a variety of compositions of clutter material, such as grass, trees, or snow (Novak et al., 1990). Our approach capitalizes on the form-sensitive operations of a neural network model in order to detect and enhance structure based on information over large, variably sized and variably shaped regions of the image.

2. Description of the Model: The neural network model used is a refinement of the Boundary Contour System (BCS) developed by Grossberg and Mingolla (1985a, 1985b, 1987) and the Feature Contour System (FCS) developed by Grossberg and Todorović (1988) through an analysis of biological vision. The BCS and FCS have been used to explain a
variety of visual effects, including brightness perception, boundary completion, hyperacuity, depth perception, neon color spreading, and binocular rivalry (Grossberg, 1987; Grossberg and Mingolla, 1985a, 1985b; Grossberg and Todorović, 1988). The BCS model locates and completes boundaries that delimit regions for filling-in with featural (color and brightness) signals. The model used for this work is similar to the BCS described in Grossberg and Mingolla (1987). The improved model adds an off-channel in the early processing, a new version of the bipole filters, and another stage in the CC Loop (defined below). The role of each processing stage is indicated in Figure 1 and explained as follows:

Stage 1 (ON Cells and OFF Cells): This stage is accomplished by two shunting center-surround systems. The first, an on-center off-surround network, corresponds to an “ON” channel of the visual pathway. Likewise, the second shunting network, with an off-center and on-surround, corresponds to an “OFF” channel. In each case the equilibrium state of the dynamical system contains both a DOG (Difference of Gaussians) term, which detects contrast differences, and a term which compensates for the level of illumination, thereby discounting the illuminant. The two networks differ in sign in their response to a given light-to-dark (left-to-right) step transition, as the ON channel responds positively on the left side of the step, and the OFF channel responds positively on the right side of the step (negative outputs are set to zero). Both channels are tuned to give a null response to uniformly illuminated areas. The outputs of the ON cells, besides feeding into Stage 2, are also employed as the FCS signals that feed into Stage 9.

Stage 2 (Simple Cells): The oriented simple cells use both the ON and OFF channels to gauge oriented contrast differences at each image location. An edge elicits a strong response in the ON channel to one side and a strong OFF channel response to the other side. Oriented outputs are calculated for twelve orientations across 180 degrees. The resulting spatial representation contains all twelve oriented outputs for every point in the original image.

Stage 3 (Complex Cells): The next level of complex cells compensates for direction of contrast by combining the rectified outputs of dark-to-light and light-to-dark simple cells at each orientation.

Stage 4 (Hypercomplex cells: First Competitive Stage): The first stage of the cooperative-competitive feedback net, or CC Loop, consists of a competition within orientation and across spatial position. This plays the role of an endstopping operation that converts complex cells into hypercomplex cells. Hypercomplex cells receive inputs from the oriented complex cells as well as positive feedback signals from long-range cooperative processes (described below). All cells also receive a tonic input which energizes disinhibitory activations of cells whose competitors are inhibited by endstopped signals.

Stage 5 (Hypercomplex cells: Second Competitive Stage): This stage is complementary to the prior stage, in that it computes a competition within position but across orientation. Here, perpendiculars to orientations inhibited in the prior stage are disinhib-
Figure 1: The BCS/FCS Model

Stage 6: Cooperative Bipole Cells

Stage 5: Hypercomplex Cells (2nd Competitive)

Stage 4: Hypercomplex Cells (1st Competitive)

Stage 3: Complex Cells

Stage 2: Simple Cells

Stage 1: ON Cells

Stage 1: OFF Cells

Stage 9: FCS Diffusion Between Boundaries

Output Stage
ited. Thus, along the sides and at the ends of lines, signals perpendicular to those received from the complex cells (Stage 3) flank the bottom-up orientation signals. These “end cuts” aid in perceptual groupings involving line ends.

**Stage 6 (Cooperative Bipole Cells):** The cooperative portion of the CC Loop is performed at this stage by bipole cells that act like long-range statistical AND gates. In order for a horizontally oriented cooperative bipole cell to fire, both the left and right receptive fields of the cell need to receive input signals from the hypercomplex cells of Stage 5. When a bipole cell fires, it sends a top-down signal through Stages 7 and 8 to the hypercomplex cells of Stage 4, where it is combined with bottom-up information. This type of boundary completion can occur simultaneously across all orientations at all positions.

**Stages 7 and 8 (Hypercomplex Cells):** Before cooperative signals are sent to the first competitive stage, a competition homologous to the first and second competitive stages takes place in order to pool and sharpen the signals that are fed back.

**Stage 9 (Diffusion in the FCS):** The BCS produces boundary signals that act as barriers to diffusion within the FCS. For the present work we have chosen to take output signals from Stage 5 of the CC Loop. Those boundary signals act to gate diffusion of signals from the ON Cells of Stage 1 at Stage 9. That is, for image pixels through which no boundary signals pass, resulting intensity values become more homogeneous over the evolution of the diffusion. Where boundary signals intervene, however, they inhibit the diffusion, leaving a resulting difference of intensity level on either side of the boundary signal.

3. **Results and Discussion:** The results of processing by BCS and FCS algorithms produce an image containing considerably less speckle (noise) than is customarily seen in SAR images. The coherence of contour information across regions spanning many pixels helps to define compartments or domains within which diffusion of signals is allowed to occur. This procedure results in a more visually pleasing and interpretable image, as regions corresponding to connected objects in the world tend to appear more homogeneous than they do in the original. This transformation is accomplished without introducing blur on the scale of objects of interest, because the BCS boundaries, acting as barriers to diffusion of signals within the FCS, help to preserve sharp transitions of image intensity in appropriate places.

It is important to note that the top image in Figure 2 is, strictly speaking, not the “original” input that is submitted to BCS/FCS processing. The signals of the true input image span five orders of magnitude and can not be adequately represented in the gray-scale of the present (paper and ink) medium. Interestingly, for appropriate choices of parameters, the shunting networks of Stage 1 can be made to accomplish a transformation very like the conventional logarithmic transformation often applied to individual pixel values of SAR imagery.
Figure 2: The top is a 400 by 300 pixel SAR image; signal amplitudes have been logarithmically transformed for display. The bottom shows the output of Stage 9 after approximately 4 hours of BCS/FCS processing on one CPU of a Silicon Graphics Iris 4D/280S. See text for details.
4. Conclusions: Analysts and photointerpreters with experience in SAR have expressed enthusiasm concerning the initial results of BCS and FCS processing. Unlike previous image enhancement approaches that rely on inference based on statistical distributions of pixel intensities or highly local filters, the present approach combines information from nonlinear oriented filters, cooperative and competitive network interactions, and diffusive filling in - processes suggested by a neural network model of human visual perception - to produce imagery that is more interpretable by human observers than has so far been produced by alternative algorithms.

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References


