1. INTRODUCTION

We have created an algorithm, which will integrate contours in real world images. The idea is to emulate the way the human brain integrates contours for visual salience in early visual pre-processing. The important components of this model are not only its abilities to find contours in an image, but for it to find contours that a human finds salient as well. Such things include contour continuity, length, closure and the uniqueness of the contour when compared to its background.

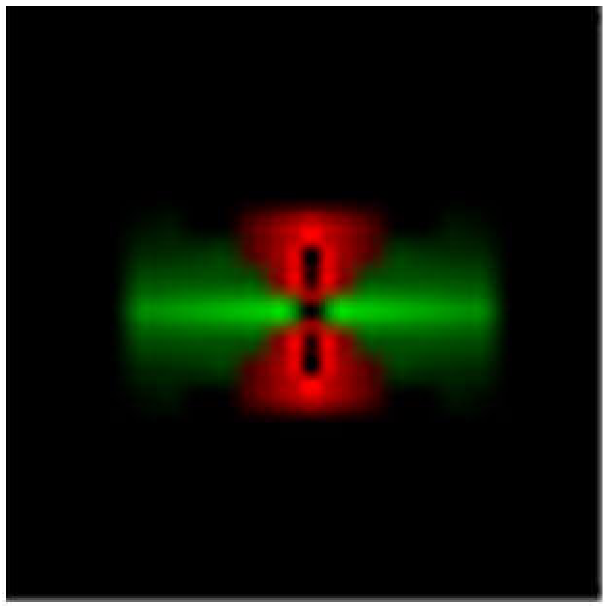

Figure 1: This shows a slice of the butterfly connection kernel. This section connects 0 degrees to 0 degrees. The green area represents excitation while the red area suppression.

Our approach has been to start with a simple model of neural connections. We use here a standard butterfly shape for connections, which has been tried with success in the past (for instance Li, 1998). The elements of the butterfly pattern are connections that branch out like wings to co-linear neurons, which creates excitation on the neurons it connects to. However, suppression is also added with a set of orthogonal wings that are used to suppress parallel contours. The end result should be that the butterfly model picks out salient contours in an image using co-linearity. However, it seems that the original butterfly shape of connections is difficult to manually tune for multiple images suggesting that the brain has adaptive centers to do this. In addition to this, the butterfly shape also does not necessarily account for contour closure or the observation that contour effects seem to extend beyond their receptive field.

To address these factors, we propose to use several devices that should aid in explaining several observed effects. We have added an adaptive layer using group suppression for when a group of neurons seems to get to excited. We have also added fast plasticity for neural weight to allow connections to dynamically adapt to local neural activity. In addition we are using the model at multi scales, which should help in preventing otherwise salient contours from being excluded.

2. MODEL

The model consists of several layers of preprocessing followed by the application of a four dimensional dynamic kernel to two orientation-filtered images. The kernel simulates the excitatory and inhibitory connections between several layers of neurons. The kernel is dynamic and changes as a result of a group suppression or fast plasticity.

An Image is taken in and is first separated into 12 images representing 12 different orientations using a standard Gabor filtering technique. Each image represents the initial image, filtered at 15 degree increments starting from 0 degrees. The image is then reduced to two different scales. Each scale will be run on the CINNIC algorithm separately. The salience map created by the two scales will then be combined in post process using a per-pixel max selector algorithm.

Convolving each oriented image against each of the other oriented images then performs the contour integration. The convolution is represented by a butterfly pattern of connections, where contour segments that are more collinear are excited while segments that are more parallel tend to suppress each other. This can be thought of as a 12-layer stack of images with each layer representing an orientation map of the image. Each neuron in each layer is connected to another neuron within its receptive field both within its layer and among the other layers. At the top of these 12 layers is a saliency map that is the sum of all the neuron/pixels below it. The top-level saliency map is itself made up of leaky integrator neurons, the output of which are filtered through a sigmoid function before viewing by the experimenter to enhance the strongest contours.

For adaptation, these neurons are also grouped together into small regional groups. If a group becomes too excited and surpasses a threshold then it is assumed that a region is too noisy. The group reacts by proportionally increasing suppression weights in the neuron layers that belong to it. Further adaptation is provided using fast plasticity. This is accomplished by increasing the weights proportionally of a single neuron for both excitation and suppression according to its level of excitation in the previous iteration. This creates not only adaptation, but creates a cascade effect as each neuron that becomes more excited subsequently excites its neighbor more, which in turn does the same to its neighbor. The end result of these techniques creates a kernel that is the product for a given neuron/pixel of the value of the pixel in two oriented maps, the value at the kernel, an additional group suppressor if applicable and a fast plasticity term.

3. RESULTS and CONCLUSION

Initially, the model had been tested on a number of both real world images as well as contour simulation images. The results at face value seemed to yield positive results. Large amounts of noise are cleaned out with the adaptive group suppression. The fast plasticity enhances the contours of the test images and the multi scale model insures that fewer contours are missed.

Quantitative analysis has also been conducted. 24 real world images representing a wide variety of contexts were used. A priori we used Photo Shop or GIMP to trace the outline of what seemed to us to be reasonable salient contours. The outline images where taken and then compared with the output images from CINNIC. It should be noted that, all images from CINNIC were run with the same values and no manual tuning was done between the time images were run.

	Correlation				Euclidian Distance			
	Mean	Max	Min	variance	Mean	Max	min	variance
Base Line	0.266	0.434	0.082	0.112	0.473	0.567	0.327	0.057
No Group Suppression	0.279	0.609	-0.223	0.218	0.518	0.878	0.354	0.129
No Fast Plasticity	0.255	0.412	-0.036	0.114	0.448	0.586	0.355	0.057
Scale at 32x32 only	0.206	0.377	0.008	0.083	0.515	0.617	0.33	0.068
Scale at 64x64 only	0.234	0.426	0.055	0.112	0.486	0.576	0.326	0.059

Table 1: These are the outcomes for the 24 images run. 5 Conditions are shown and two different methods were used to asses fitness.

Analysis was done between the test image and CINNIC output image for all 24 images using Euclidian distance as well as linear regression correlation under several different conditions. Without group suppression the mean Euclidian distance was poorer. Also, the variance was twice as much without group suppression for both correlation and Euclidian Distance suggesting that group suppression increases the consistency of outcomes. Fast plasticity also seemed to help. Without fast plasticity the minimum correlation was negative among the 24 images. However, with fast plasticity, all correlational values were positive.

The data also supports the notion of improvement from the use of multi scales. Each of the scale images by themselves was compared with the outline images. In neither case did the mean correlational value or Euclidian distance surpass the values of the final max selected composite image.

Qualitative analysis suggests that CINNIC has an affinity for longer straighter contour segments with greater continuity, which seems to agree with literature on contour integration. CINNIC is also more effective at finding contours that are more unique given its region, as is also suggested by literature on contour integration. CINNIC's abilities with closure effect are currently being assessed, but the data regarding it as of yet is not conclusive.

4. REFERENCES

Li, Z. (1998) A neural model contour integration in the primary visual cortex *Neural comput.* 10, 903-940