SPIKING HIERARCHICAL NEURAL NETWORK FOR CORNER DETECTION

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Abstract: To enable fast reliable feature matching or tracking in scenes, features need to be discrete and meaningful, and hence corner detection is often used for this purpose. We present a new approach to corner detection inspired by the structure and behaviour of the human visual system, which uses spiking neural networks. Standard digital images are processed and converted to spikes in a manner similar to the processing that is performed in the retina. The spiking neural network performs edge and corner detection using receptive fields that are able to detect edges and corners of various orientations. The locations where neurons emit a spike indicate the positions of detected features. Results are presented using synthetic and real images.

1 INTRODUCTION

Previous research has illustrated that edges, contours and corners are very important for visual perception (Shapley and Tolhurst, 1973). Many derivative-based feature detection operators have been proposed in the past 30 years, in particular many detectors have been proposed to detect edge junctions and corners. Moravec (1977) developed a corner detector that shifted a small square window in vertical, horizontal, and diagonal directions. Harris and Stephens (1988) expanded the Moravec operator, removing the limitation of discrete window shifts, to develop a combined corner and edge detector. The operator response determines whether the detected feature is a corner, edge, or a flat region. Smith and Brady's SUSAN corner detector (Smith and Brady, 1997) is based on brightness comparisons over neighbourhoods and the detector can distinguish both corner and edge pixels. Shen and Wang (2001) have expanded a local edge detector so that corners may also be detected.

However, when comparisons are drawn between the performance of such artificial vision feature detectors and the processing capabilities of the human visual system (HVS) it becomes apparent that current approaches suffer serious weaknesses. Recently researchers have started to examine the possibility of using biologically inspired image processing techniques. In the HVS a visual scene is processed starting in the retina where light intensity is converted into nerve signals within the photoreceptors. These signals are then pre-processed and propagated through the various layers within the retina with varying delays and lateral inhibition onto the retinal ganglion cells. The majority of the resulting spike train output from the retinal ganglion cells travels along the optic nerve for further processing in the lateral geniculate nucleus (LGN), and other areas of the brain. Biological research has shown that the brain deals with information processing by using a complicated network of neurons (Hodgkin and Huxley, 1952). The process of simulating biological information processing in engineering is termed neuro-engineering (O'Connor, Huber and Svoboda, 2008) and such techniques are typically used for artificial intelligent systems.

Spiking neural networks (SNNs) are a new class of artificial neural network that mimic biological information processing in the brain more accurately than traditional neural networks. However there are very few attempts to use SNNs to model aspects of the human visual system. In (Van Rullen and Thorpe, 2002) scene categorisation is performed and this work is then expanded in (Masquelier and Thorpe, 2010) to perform object recognition. In (Escobar, Masson, Vieville and Kornprobst, 2009) a SNN is used to model two areas of the brain concerned with motion, with the aim of action recognition. A SNN model is

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proposed in (Meftah, Lezoray and Benyettou, 2010) that performs segmentation and edge detection. In (Chevallier et al., 2006) a distributed SNN is proposed for extracting saliencies in an image and in (Hugues et al., 2002) contours are detected in images through the synchronisation of integrate and fire neurons. SNN approaches have also recently been applied for the purpose of image segmentation, in (Wu et al., 2007a) which has proven to be fast and efficient. However, these approaches focus on edge or contour detection but to a lesser extent, corner or interest point detection. In (Wu et al., 2007b) a SNN was proposed that detected right angle corners only.

In this paper we present a SNN approach to corner detection. Our approach is based on a biologically inspired hierarchical structured SNN that is capable of detecting various features (edges and corners). The network uses difference of Gaussian filters, replicating the retinal ganglion cells in the retina, for converting images to spikes. Receptive fields are formed using a hierarchical structure, with inputs from two types of retinal ganglion cells that are capable of detecting edges and corners. The network detects corners at angles of 45 and 90 degrees.

In Section 2 we present the neuron model used in the simulations and in Section 3 we present our spiking neural network structure. Experiments and results are presented in Section 4 with discussion and further work presented in Section 5.

2 SPIKING NEURON MODEL

Biological neurons use short and sudden increases in voltage (commonly known as action potentials, spikes or pulses) to send information. The first scientific model of a spiking neuron, proposed by Hodgkin and Huxley (1952), is based on experimental recordings from the giant squid axon using a voltage clamp method. The complexity in simulating the model is very high due to the number of differential equations and the large number of parameters. Thus, most computer simulations choose to use a simplified neuron model such as the integrate-and-fire model (I&F). The I&F model models the state of the neuron by its membrane potential, which receives excitatory or inhibitory signals from synaptic inputs from other neurons. Each input is weighted by its associated synaptic strength. The leaky I&F model produces a more biologically realistic neuron model adding a "leak" term to the membrane potential, reflecting the diffusion of ions that occurs through the membrane when some equilibrium is not reached in the cell. For implementation purposes, the leaky I&F model has been selected to model the network neurons in this paper. A full review of the biological behaviour of single neurons can be found in (Gerstner and Kistler, 2002) and a comparison of different neuron models can be found in (Izhikevich, 2004).

3 NETWORK STRUCTURE

In a biological system a receptive field is where a spiking neuron integrates the spikes from a group of afferent neurons as illustrated in Figure 1 where neuron N has a receptive field with a 9 neuron array. Each neuron in the receptive field connects to neuron N through both excitatory and inhibitory synapses.

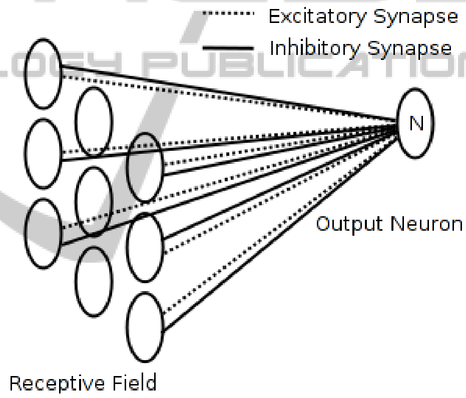


Figure 1: Receptive field of a spiking neuron.

We construct a spiking neural network using receptive fields with the leaky I&F neuron model (outlined in Section 2). Within the network structure proposed we have four processing layers corresponding to the receptor layer, the edge detection layer, the corner detection layer, and the output layer. We define our spiking neural network structure as illustrated in Figure 2. The first layer in the network represents the retinal ganglion cells found in the retina. Here the input image mimics the On-Centre Off-Surround and Off-Centre On-Surround ganglion cells found in the retina by convolution with difference of Gaussian (DoG) filters. This layer produces two images that are converted into spike trains in the time domain. In summary the conversion from input image to spike trains involves converting the DoG responses to spike trains where high DoG responses correspond to spike trains with short delays and low DoG responses correspond to spike trains

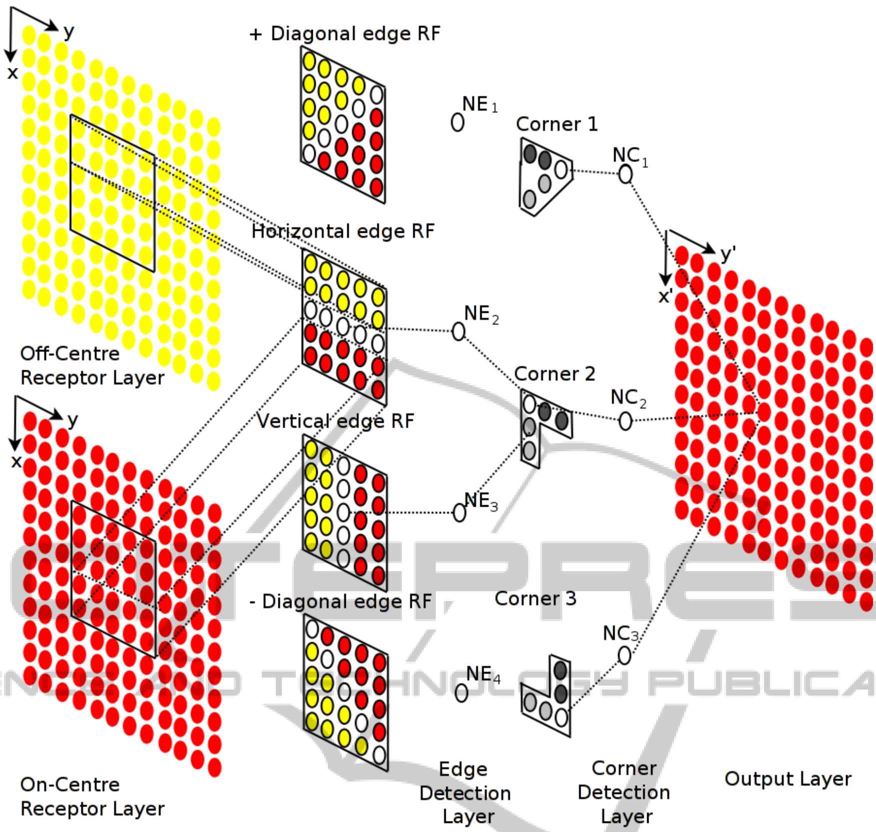


Figure 2: Spiking Neural Network Structure.

with long delays. The highest output from the DoG filtered images are areas where the image intensity changes rapidly, corresponding to the most rapidly firing neuron. Zero or negative DoG responses are areas where the image intensity remains constant corresponding to the slowest firing neurons

Due to the nature of the On-Centre Off-Surround and Off-Centre On-Surround images any neurons that fire slow in one image fire rapidly in the other, and vice-versa as the images are inverses of each other. Thus, areas of interest in the images, such as a rapid change in intensity can be detected with a change in the firing rate of neurons in a particular region. To detect this change in firing rate between images we construct receptive fields of various orientations that receive input on either side from the On-Centre and Off-Centre images. If the receptive field has all the neurons firing rapidly i.e. both sides of the receptive field, this corresponds to an area of the image with rapidly changing intensity, such as an edge.

In this work we define the edge detection layer with four types of neurons corresponding to four different receptive fields respectively. There are four parallel arrays of neurons in the edge detection layer each of the same dimension as the Receptor layer with only one neuron (labeled NE_x) in each array illustrated in Figure 2 for simplicity. Each of these layers performs the processing for a different edge direction and is connected to the receptor layer by differing weight matrices. The receptive field receives input on either side from both the On- Centre and Off-Centre receptor level inputs. The arrangement of the inputs determines the edge orientation that may be detected. In the experiments presented here we have four types of edge receptive fields corresponding to horizontal, vertical, and both diagonal directions. The synaptic weights for all the edge detection receptive fields are identical and are chosen heuristically.

The corner detection layer is composed of eight types of neurons and performs in a similar manner to the edge detection layer. The inputs to the corner detection neurons are the outputs from the edge detection neurons at different orientations. The arrangement of the inputs determines the type of corner that may be detected. Each corner detection neuron has a receptive field formed by different edge detection neurons. For example, in Figure 2 we illustrate that the corner detection neuron NC_2 forms a receptive field with edge detection neurons NE_2 and NE_3 corresponding to horizontal and vertical edges respectively. Thus actual connectivity of the synapses within the receptive field defines the type of corner the neuron can detect. In Figure 2 we have illustrated three types of corner detection receptive fields for visual clarity. The synaptic weights for all the corner detection receptive fields are identical and are chosen heuristically.

The output layer integrates all the responses from the corner detection layer and produces a firing map. The corner neuron firing map indicates those neurons that have reached each individual neuron's firing threshold and thus produced a spike. Hence, a corner point is detected at a location where a neuron in the corner detection layer has fired at least one spike. For visual clarity detected points are superimposed over the original image in the presented results. The network model was implemented with the *Brian* simulator (Goodman and Brette, 2009) using a standard leaky I&F model with parameters that are consistent with biological neurons (Gerstner and Kistler, 2002).

4 EXPERIMENTS AND RESULTS

In order to test the performance of our proposed spiking neural network we construct a synthetic image with two rectangular shapes at different orientations. The image intensities used to construct the step edges in the synthetic image are 100, 129, and 158 (where the possible range of intensities is [0-255]) and the image size is 45×45 pixels. In the case of the orientated rectangle shape the intensities are obtained through bilinear interpolation using the same step edge intensities, the synthetic image is presented in Figure 3.

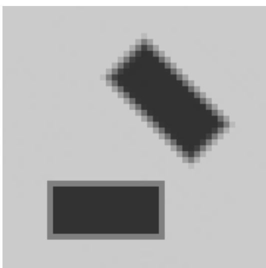
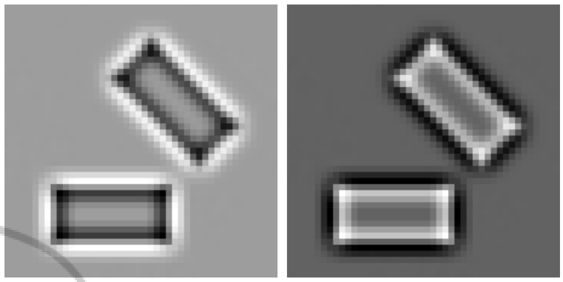


Figure 3: Example synthetic input image.

As described in Section 3 we then convolve the input image with DoG filters, mimicking the On-Centre Off-Surround and Off-Centre On-Surround ganglion cells found in the retina and the outputs after convolution with the two DoG filters are illustrated in Figure 4.



(a) On-Centre Off-Surround

(b) Off-Centre On-Surround

Figure 4: Example retinal ganglion cell filtered image.

The retinal ganglion cell images are converted into spike trains. Figure 5 illustrates an example raster plot for the spike activities of the image in Figure 4(a). In Figure 5, individual neurons are represented on the *y*-axis and the *x*-axis represents the spike activities of each neuron over the simulation time. This spike raster plot illustrates that in areas of the retinal ganglion cell image with negative or zero values no spikes are produced and in areas of the retinal ganglion cell image with the strongest responses the corresponding neuron fires rapidly.

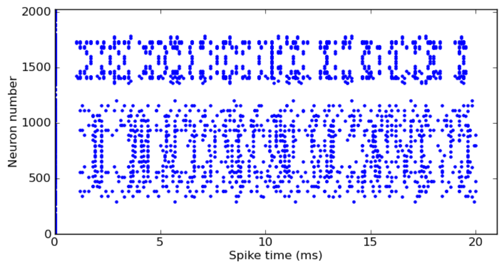
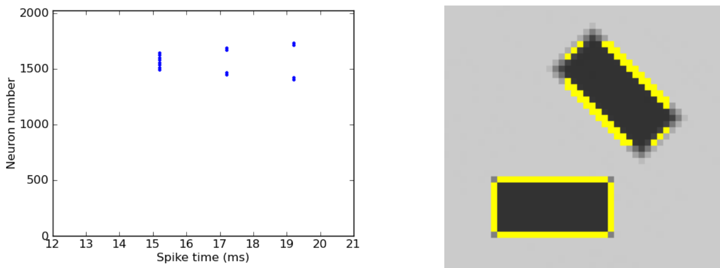


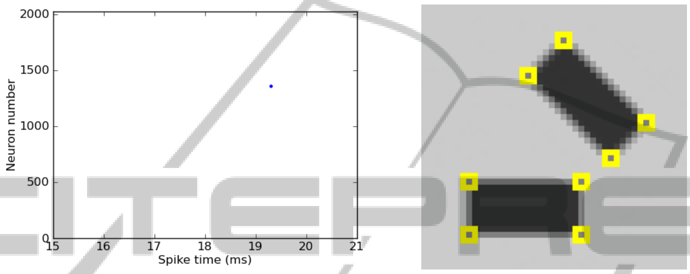
Figure 5: Example spike trains computed from On-Centre Off-Surround ganglion cell image.

The On-Centre and Off-Centre image spike trains are presented to the hierarchical network and processed by the edge detection layer using the receptive fields. This layer then provides input to the corner detection layer. To illustrate the performance of the edge detection layer we show an example output raster plot for the horizontal edge in Figure 6(a) and the combined outputs from the edge detection layer translated to image positions highlighted over the original input image in Figure 6(b). The spikes output from the edge detection layer are then input into the corner detection layer where the various types of receptive fields process them in order to perform



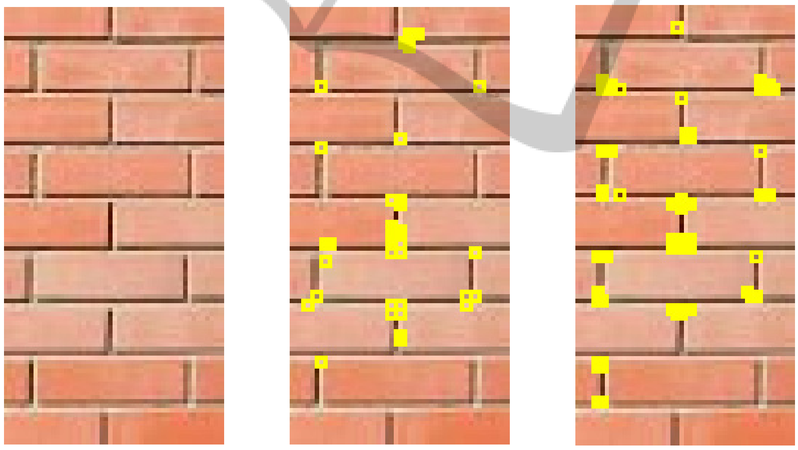
(a) Firing neurons for horizontal edge (b) Edge neurons firing locations

Figure 6: Example neurons firing in edge detection layer.



(a) Firing neurons for corner type 1 (b) Corner neurons firing locations

Figure 7: Example neurons firing in corner detection layer.



(a) Input image (b) SNN Corner detector (c) Harris Corner detector

Figure 8: Example output from simple real image.

corner detection. The outputs from the corner detection layer are then integrated in the output layer where neurons are tuned to fire upon receiving a spike from any neuron in the corner detection layer.

In Figure 7(a) we illustrate the output raster plot for all neurons connected to one particular type of corner detection receptive field (in this case a 90° corner orientated between 90°-180°). There is only one spike firing in the raster plot indicating that there is only one particular type of corner present corresponding to that type of neuron in the image.

The outputs from all the corner neurons that have fired in the corner detection layer are illustrated in Figure 7(b) where the firing neurons have been transformed into image locations and marked where the centre of the square is the firing neuron location. We have also applied the network to a simple real image to examine its performance in comparison to the standard corner detection algorithm of Harris and Stephens (1988), as illustrated in Figure 8. This visual comparison illustrates the SNN provides similar results to the Harris corner detector (with a threshold equal to 120) and in some cases the corners are more accurately located using the SNN approach than the Harris corner detector.

5 DISCUSSION AND FUTURE WORK

The spiking neural network presented in this paper is constructed using a hierarchical structure that is composed of spiking neurons with various receptive fields. The input image is converted to retinal ganglion cell output spike trains by convolving with DoG filters. The spike trains are presented to the network and the various receptive fields process the image, performing edge detection and corner detection. The spiking neuron models provide powerful functionality for integration of inputs and generation of spikes. Synapses are able to perform different complicated computations. This paper demonstrates how a spiking neural network can detect edge and corners in an image. The performance illustrates that the proposed detector is currently only capable of detecting simple edges at specific orientations and similarly only particular corner types. However, the current results appear promising when compared with the standard Harris approach to corner detection. Future work will involve the incorporation of biologically plausible unsupervised learning algorithms (STDP) to set the synaptic weights, automatic development of receptive fields to deal with different edge and corner types.

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