BIOLOGICALLY INSPIRED EDGE DETECTION USING SPIKING NEURAL NETWORKS AND HEXAGONAL IMAGES

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Keywords: Spiking neural network, Edge detection, Multi-scale hexagonal receptive fields.

Abstract: Inspired by the structure and behaviour of the human visual system, we extend existing work using spiking neural networks for edge detection with a biologically plausible hexagonal pixel arrangement. Standard digital images are converted into a hexagonal pixel representation before being processed with a spiking neural network with scalable hexagonally shaped receptive fields. The performance is compared with different sized receptive fields implemented on standard rectangular images. Results illustrate that using hexagonal-shaped receptive fields provides improved performance over a range of scales compared with standard rectangular shaped receptive fields and images.

1 INTRODUCTION

The human vision system (HVS) processes a visual scene starting in the retina where light intensity is converted into nerve signals within the photoreceptors. The signals are pre-processed and propagated through the various layers within the retina. The resulting spike train output from the retinal ganglion cells travels along the optic nerve for further processing in the lateral geniculate nucleus and visual cortex. The powerful performance of the HVS is achieved through massive parallel processing using neurons and their complex interconnections formed by synapses. Taking inspiration from the HVS research has tried to improve image processing techniques, via the use of neural networks (NNs) (Egmont-Petersen et al., 2002). Spiking neural networks (SNNs) are a class of NNs that mimic more accurately the biological information processing in the brain. Using a temporal coding scheme SNNs improve upon NNs increasing computational power, speed and therefore enabling real-time processing (Kunkle and Merrigan, 2002). SNNs use simple neuronal models and communicate using spikes in a manner similar to action potentials found in biological neurons. In (Wu et al., 2007); (Meftah et al., 2008); (Buhmann et al., 2005) SNN approaches have been developed for image segmentation. In (Escobar et al., 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 proposed in (Meftah et al., 2010) that performs segmentation and edge detection, however images must first be segmented before the edge detection stage can be performed. A SNN is proposed in (Hugues et al., 2002) to detect contours in images through the synchronisation of integrate and fire neurons using simple synthetic images. In (Wu et al. 2007) a SNN is proposed for real-time edge detection. In (Chevallier et al., 2006) a distributed SNN is proposed for extracting saliencies in an image and in (Chevallier and Dahdouh, 2009) a SNN is used to perform Difference of Gaussian filtering. In (Delorme and Thorpe, 2003) a SNN is proposed that uses a rank order coding scheme.

In computer vision the apparent strength of a feature in an image may depend on the scale at which the appropriate feature detection operator is applied and many standard approaches to multi-scale feature detection have been developed (Lindeberg, 1994). However, scalable feature extraction algorithms using bio-inspired approaches have been researched and developed to a much lesser extent with the exception of the approach by (Gao et al., 2006) where a NN that simulates the multi-scale receptive field of the biological vision is proposed. In this paper we present a novel approach to feature extraction using scalable receptive fields.

Clogenson M., Kerr D., McGinnity M., Coleman S. and Wu Q. (2011).
BIOLOGICALLY INSPIRED EDGE DETECTION USING SPIKING NEURAL NETWORKS AND HEXAGONAL IMAGES.
In *Proceedings of the International Conference on Neural Computation Theory and Applications*, pages 381-384
DOI: 10.5220/0003682103810384

Within the fovea the cone photoreceptors are tightly packed into a hexagonal lattice, resulting in photoreceptors that are generally surrounded by 6-neighbours (small irregularities occasionally exist). Most existing methods for feature extraction are based on rectangular lattices. Allen (2003) has shown that curved structures are not well represented on a rectangular lattice leading us to question why we use them when nature has chosen a hexagonal lattice for photoreceptors? Using an artificial hexagonal sampling lattice, both spatial and spectral advantages may be derived: namely, equidistance of all pixel neighbours and improved spatial isotropy of spectral response. Pixel spatial equidistance facilitates the implementation of circular symmetric kernels that are associated with an increase in accuracy when detecting straight and curved edges (Allen, 2003). Better spatial sampling efficiency is achieved by the hexagonal structure compared with a rectangular grid of similar pixel separation, leading to improved computational performance. A hexagonal grid with unit separation of pixel centres has approximately 13% fewer pixels than the same image resolution on a rectangular grid with unit horizontal and vertical separation of pixel centres (Vitulli, 2002).

In this paper we present a biologically inspired approach to feature extraction using spiking neural networks, hexagonal pixel-based images that mimic the hexagonal arrangement found in the retina, and scalable hexagonally arranged receptive fields.

2 MODEL IMPLEMENTATION

We use a method proposed in (Middleton and Sivaswamy, 2001) to create hexagonal pixels (and images) from clusters of sub-pixels which limits the loss of image resolution whilst complying with the main hexagonal properties (Middleton and Sivaswamy, 2001). The hexagonal pixel is comprised of 56 sub-pixels closely representing the shape of a single hexagonal pixel, thus enabling us to mimic the hexagonal structure used by the HVS for image capture.

We define our spiking neural network structure as illustrated in Figure 1. Suppose that the first layer represents photoreceptors where each pixel in the hexagonal image corresponds to a photoreceptor. A receptive field is where a spiking neuron integrates the spikes from a group of afferent neurons, and in our model this intermediate layer is composed of four types of neurons corresponding to four different receptive fields respectively.

Each of the four parallel arrays of neurons in the intermediate layer are the same dimension as the receptor layer with only one neuron in each array illustrated in Figure 1 for simplicity. Each of these layers performs the processing for different edge directions and is connected to the receptor layer by differing weight matrices. These weight matrices can be of varying sizes to represent the width of the receptive field under consideration. We use the conductance-based integrate-and-fire spiking neuron model as this offers biological realism whilst providing a reduction in computational complexity (Izhikevich, 2004). ‘X’ in the synapse connections represents an excitatory synapse and ‘Δ’ represents an inhibitory synapse. Each neuron in the output layer integrates four corresponding outputs from intermediate neurons. The firing rate map of the output layer forms an edge graphic corresponding to the input image. The receptive fields illustrated in the intermediate layer in Figure 1 can be receptive fields of any size and we will use 7, 19, and 37-point hexagonal receptive fields.

The network model was implemented in Matlab using the network parameters found in (Wu, et al., 2007) that are consistent with biological neurons (Masland, 2001). Synapse strengths can be adjusted to ensure that the neuron does not fire in response to a uniform image within its receptive field.

3 RESULTS AND EVALUATION

We present edge detection results at three different scales using 7- 19- and 37-point sized hexagonal receptive fields (denoted as HSNN-7, HSNN-19 and HSNN-37). For comparison we also present results using the SNN approach in (Wu et al., 2007) which uses a standard rectangular structure (denoted as SNN). In Figure 2 we present the edge maps generated by using the well known Lena image as input to the SNN models. The edge brightness increases as the firing rate of the neuron becomes stronger, thus the firing rate may be set as a threshold to determine the presence or absence of an edge. The output from the HSSN is much clearer and less noisy than the corresponding output from the SNN.

We evaluate the performance of both the HSNN and SNN approaches using the Figure of Merit (FOM) technique (Abdou and Pratt, 1979) in Figure 3. The FOM is compared over a range of noise levels. Figure 3 illustrates that the HSNN shows improved performance over the SNN for all edge types, in particular in areas of high noise and this is

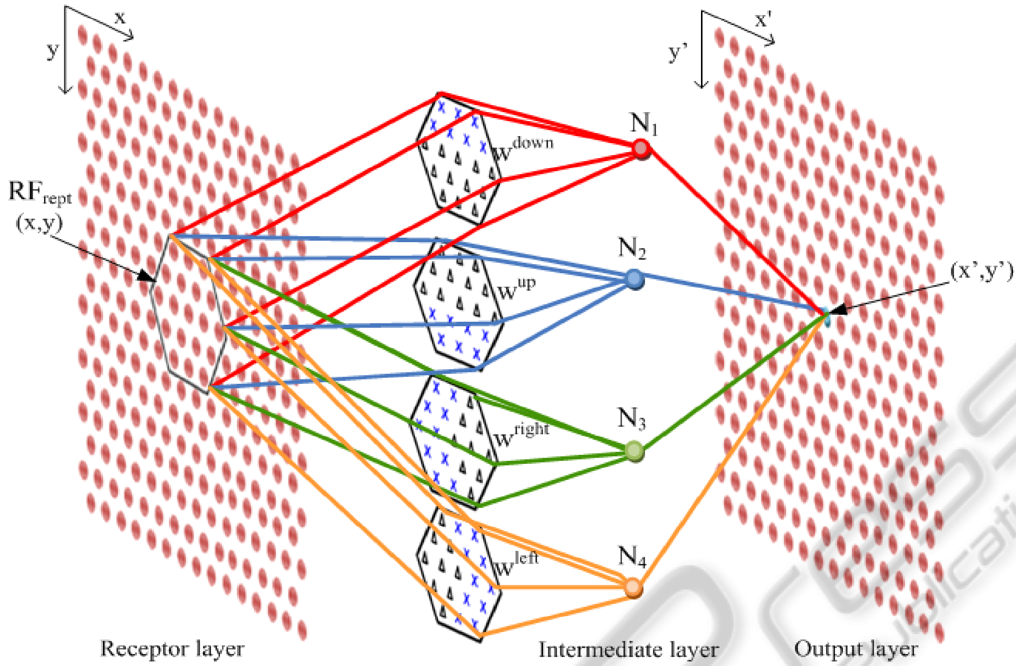
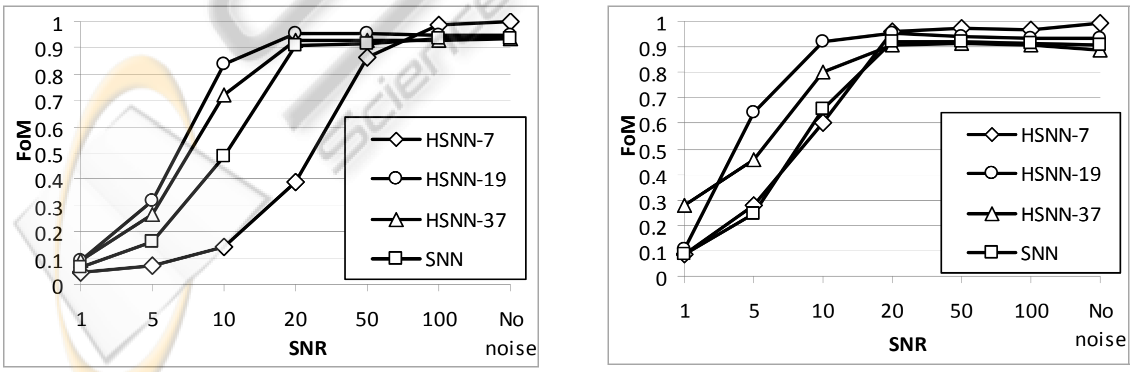


Figure 1: Spiking Neural Network Structure.

(a) SNN (Wu et al., 2007). (b) 7-Point HSNN (c) 19-Point HSNN (d) 37-Point HSNN

Figure 2: Example Edge Detection Outputs.



(a) Vertical edge (b) Diagonal edge

Figure 3: Figure of Merit result.

becomes more evident as the receptive field size increases. The simulation is run and spikes are computed over a time interval of 100ms. Table 1 compares the time to run this simulation and illustrates an improvement in computation time with the hexagonal arrangement.

Table 1: Algorithm run times (seconds).

RF Size	Processing time
SNN	3.92
HSNN 7-Point	3.16
HSNN 19-Point	3.47
HSNN 37-Point	3.78

4 DISCUSSION AND FUTURE WORK

We present a biologically inspired approach to feature detection that is mimics the human visual system. The presented SNN is constructed by a hierarchical structure that is composed of spiking neurons with various receptive fields. The input image has a hexagonal pixel arrangement and correspondingly the receptive fields used are also arranged in a hexagonal structure. 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 edges in an image using a hexagonal structure over a wide range of scales and demonstrates performance and computational improvements over rectangular pixel-based SNN approaches.

ACKNOWLEDGEMENTS

This work was supported by the Centre of Excellence in Intelligent Systems project, funded by InvestNI and the Integrated Development Fund.

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