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An Introduction to Third Generation of Neural Networks for Edge Detection

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Abstract

Being inspired by the structure and behavior of the human visual system the spiking neural networks for edge detection comes in existence. Edge detection is one of the most important factor in image analysis whose goal can be regarded as to find edges present in an image. ANN has been developed so far. Later a network model based on spiking neurons is proposed for edge detection Spiking neuron networks (SNNs) which are often referred to as the third generation of neural networks and have potential to solve problems related to biological stimuli. SNNs improve the representation capacity and the processing abilities of neural networks. SNN is able to perform edge detection within a processing time is consistent with human visual system. This paper presents a concept that how SNN can be applied for edge detection.

Introduction

Edge detection is the process of identifying and locating sharp discontinuities in an image. Edges are places in the image with strong intensity contrast. Representation of an image by its edges has advantage that the amount of data is reduced significantly while retaining most of the image information.The human visual system plays an important role in terms of visual judgement over traditional computer vision techniques. It is preferred by Neurobiologist and computer scientists. Receptors in eye retina are useful for resolving fine details of an image because each one is connected to its own nerve cell. This performance lies in neural structure which is very complex and still not fully understandable.

Thus taking idea from human vision system research has carried out to improve image processing techniques using neural network [3]. Spiking neuron networks (SNNs) which are often referred to as the third generation of neural networks used for processing the biological information in brain. Spiking neural network is useful in real time processing which uses temporal coding scheme and hence improving processing speed and computational power [3].The important characteristics of SSN is the information processed is encoded by the spikes.

Various network models have been proposed for explaining the visual system able for image processing. The basic spiking neuron model for the visual cortex has been developed using Hodgkin and Huxley equation[1].Many Spiking neuron models have been developed nowadays for image processing such as leaky integrate and fire model ,spike response model, conductance based I&F model etc. In this paper an approach to edge detection by using spiking neural networks is explained.

Creating the Hexagonal Image

In present scenario no hardware is commercially available to capture or display hexagonal images and therefore a resampling technique [5] must be applied to generate hexagonal pixel based images. Many resampling techniques exist for this purpose; here we use the technique proposed in [9] in which Middleton enhances Wuthrich's method of creating a pseudo hexagonal pixel from a cluster of square pixels by representing each pixel by a pixel block in order to create a sub-pixel effect which enables the sub-pixel clustering; this limits the loss of image resolution whilst complying with the main hexagonal properties. Selection of the number of pixels to be clustered for each hexagonal pixel is based on two issues: the arrangement must allow a tessellation with no overlap and no gaps between neighboring hexagonal pixels; and the cluster must closely resemble a hexagon i.e. six sides of approximately equal length. In [10], two possible choices of hexagonal pixel representations are presented: in one case the hexagonal pixel is comprised of 30 sub-pixels, in the other case it is comprised of 56 sub-pixels; we have chosen to use the 56 sub-pixel approach as illustrated in Fig. 1. To avoid a high loss in image resolution when using this technique each original pixel is separated into a 7×7 block of sub-pixels having the same intensity as the original pixel. Each hexagonal pixel is then created by clustering 56 of these sub -pixels together with its intensity being calculated as the average intensity of the 56 sub-pixels. The image resizing also enables the display of sub pixels, and therefore the display of hexagonal pixels.

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When comparing the size of these generated hexagonal hyper-pixels with the original square pixels, the hexagonal pixels are 12.5% larger than the square pixels. Thus the resampled image has the same resolution as the original image but the number of hexagonal pixels necessary to tessellate an image plane is 12.5% less than it would take using square pixels. With this structure now in place, a cluster of sub pixels in the new image, closely representing the shape of a hexagon, can be created that represents a single hexagonal pixel in the resized image.

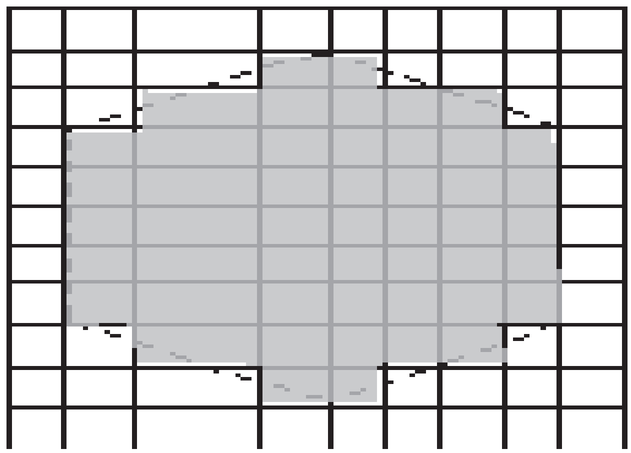

Figure 1. 56 sub-pixel cluster

Spiking Neural Network for Edge Detection

The human visual system performs edge detection very efficiently. Neuroscientists have found that there are various receptive fields from simple cells in the striate cortex to those of the retina and lateral geniculate nucleus and the neurons can be simulated by the Hodgkin and Huxley neuron model [1]. Based on these receptive fields and the neuron model, a network model is proposed to detect edges in a visual image in this paper.

Receptive field in biological system is a group of afferent neurons where spiking neurons integrates and spike.

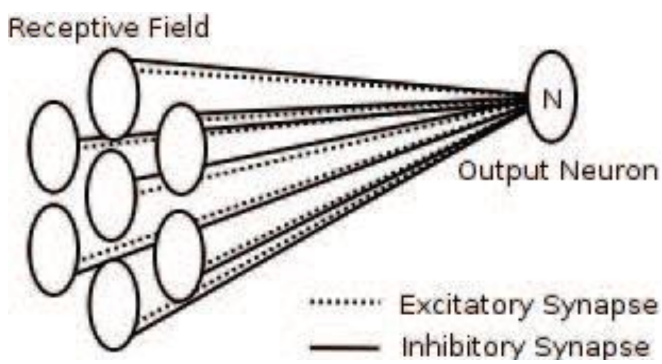

Figure 2. Receptive field of a spiking neuron.

From Figure2, each neuron in receptive field connection to neuron N through both excitatory and inhibitory synapses. The HVS detects the edges in image effectively by using various receptive fields from simple cells in the cortex. These neurons can be simulated by basic spiking neuron model proposed by the Hodgkin and Huxley equation [1].

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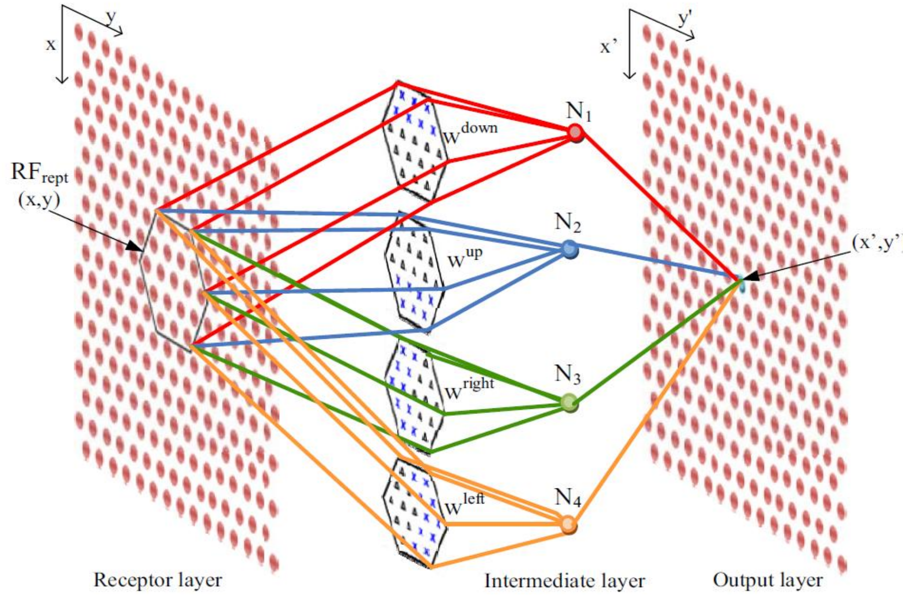

Figure 3. Spiking Neural Network Structure

A network model based on receptive fields is proposed to detect edges in a visual image as shown in Figure3. This figure consists of three layers. Suppose that first layer represent photoreceptor in which every pixel in hexagonal image corresponds to a photoreceptor.The intermediate layer is composed of four types of neurons corresponds to four different receptive fields respectively. 'X' in the synapse connections represents an excitatory synapse. 'Δ' represents an inhibitory synapse.

There are four parallel arrays of neurons in the intermediate layer each of the same dimension as the Receptor layer. These arrays are flagged as N1, N2, N3 and N4 and only one neuron in each array is shown in Figure 1 for simplicity. Each of these layer performs the processing for diff edge detection and is connected to receptor layer by diff weight matrices can be of varying sizes to represent width of receptive field under consideration.. Neuron (*x'*, *y'*) in the output layer integrates the outputs from these four neurons from the intermediate neuron .The firing rate map of output provides an edge corresponding to the input image.

The receptive fields explained in the intermediate layer consist of rectangular arrangement [1].Recent neurological research shows that better sampling efficiency is achieved by the hexagonal structure because of having unit separation of pixels centers' has approximately 13% fewer pixels than the same image resolution on the rectangular arrangement with unit horizontal and vertical separation of pixels[3].

Spiking Neuron Model

There are many different schemes for the use of spike timing information in neural computation. The integrate-and-fire model, which is very commonly used in networks of spiking neurons. This model is simple to understand and implement. However, as it approximates the very detailed Hodgkin-Huxley model very well it captures generic properties of neural activity. The most widely used and best-known model of threshold fire Neurons, and spiking neurons in general, is the integrate and-fire neuron..A spike travels down the axon and is transformed by a low-pass filter, which converts the short pulse into a current pulse I(t-tj(f)) that charges the integrate-and-fire circuit. The resulting increase in voltage there can be seen as postsynaptic potential *ε (t-tj (f))*. Once the voltage over the capacitor goes above threshold value and the neuron sends out a pulse itself. Mathematically it can be explained as

$$\tau_m \frac{\partial u}{\partial m} = -u\ (t) + RI\ (t)$$

to describe the effects on membrane potential *u* over time, 'leaks' away. As with the spike-response model the neuron fires once *u* crosses threshold and a short pulse δ is generated. To force a refractory period after firing we set *u* to *K*<0 for a period of δ abs.

$$I_i(t) = \sum_{j \in \Gamma_i} c_{ij} \sum_{t_j^{(f)} \in F_j} \delta(t - t_j^{(f)})$$

The input current I for neuron $\boldsymbol{i}$ will often be 0, as incoming pulses have a finite short length. Once a spike arrives, it is multiplied by synaptic efficacy factor *Cij* forming the postsynaptic potential that charges the capacitor. This model is computationally simple [6]. The most widely used spiking neuron model was developed from Hodgkin and Huxley's work [1] based on experimental recordings obtained from experiments on the giant squid axon using a voltage clamp method. However, even though this model is biologically plausible, the complexity in simulating the model is very high due to the number of differential equations. Thus, most computer simulations of neuron models choose to use a simplified neuron model such as the integrate-and-fire model (I&F), leaky I&F model, conductance-based I&F or Izhikevich's model. A full review of the biological behaviour of single neurons can be found in [6] and a comparison of different neuron models can be found in [7]. For implementation purposes the conductance-based I&F model has been selected to model the network neurons in this work. This model offers similar neuron behaviour to the Hodgkin-Huxley whilst providing a reduction in computational complexity. In the conductance-based I&F model the membrane potential $v(t)$ is governed by the following equation:

$$c_m \frac{dv(t)}{dt} = g_l\left(E_l - v(t)\right) + \frac{w_{ex} g_{ex}(t)}{A_{ex}}\left(E_{ex} - v(t)\right) + \frac{w_{ih} g_{ih}(t)}{A_{ih}}\left(E_{ih} - v(t)\right)$$

where $\boldsymbol{C_m}$ is the membrane capacitance, $\boldsymbol{E_1}$ is the membrane reversal potential, g_1 is the conductance of the membrane, $\boldsymbol{E_{ex}}$ and $\boldsymbol{E_{ih}}$ are the reversal potential of the excitatory and inhibitory synapses respectively, $\boldsymbol{w_{ex}}$ and $\boldsymbol{w_{ih}}$ are weights for excitatory and inhibitory synapses respectively, and $\boldsymbol{A_{ex}}$ and $\boldsymbol{A_{ih}}$ are the membrane surface area connected to the excitatory and inhibitory synapses respectively. If the membrane potential $v(t)$ exceeds the threshold voltage $\boldsymbol{v_{th}}$ an action potential is generated and then $\boldsymbol{v(t)}$ is reset to v_{reset} for a time τ_{ref} which is called the refractory duration. For simplicity τ_{ref} is set to 0 in this paper. The variables $\boldsymbol{g_{ex}}$ $\boldsymbol{(t)}$ and $\boldsymbol{g_{th}(t)}$ represent the conductance's of excitatory and inhibitory synapses respectively, which vary with time. The output spike train is then represented by a series of 1s or 0s representing whether or not a neuron fires at time t, i.e.

$$[S_{out}(t_1), S_{out}(t_2), \ldots, S_{out}(t_M)]$$

Conclusion

The spiking neural network presented in this paper is the review of hierarchical structure that is composed of spiking neurons with various receptive fields. The input image has a hexagonal pixel arrangement and the receptive fields used are 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 also demonstrates how a spiking neural network can detect edges in an image using a hexagonal structure and illustrates performance and computational improvements over the standard square based approaches.

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