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Edge Detection Techniques: Analysis for Contrasting Recent and Conventional Approach

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Abstract— This paper depicts three methods for edge detection. The first method is one of the promising method for edge detection based on canny edge detection. In the second method neural network has been used for edge detection. Third method is inspired by the behavior of biological receptive fields and the human visual system. A network model based on spiking neuron is proposed to detect edges in visual image. SNN is able to perform edge detection within a processing time which is consistent with human visual system. SNNs improve the representation capacity and the processing abilities of neural networks. Successful computer simulation results are obtained.

Index Terms—Edge detection, spiking neural network, Human visual system, Peak signal to noise ratio, Mean square error.

I. INTRODUCTION

Edge detection play an important role for characterizes the boundaries of object. It contains important information of object and use to distinguish different objects and separate them from background in a scene. Representing an image by its edges has the further advantage that the amount of data is reduced significantly while retaining most of the useful image information. This data is processed in image segmentation, feature extraction, pattern recognition and image analysis and computer vision. Edge detection is useful for mark the points in the digital image. Several algorithm are developed for detecting the edges of an digital image. Canny edge detection algorithm was developed by John F. Canny in 1986[1]. The quality of edge detection is depends on lighting conditions, change in intensities function approximation capabilities of neural networks, Artificial neural networks can be useefficiently over conventional edge detection approaches such as canny operator, laplacian method etc[4]., density of edges in an image and noise[2].Referring to the

Taking an idea from human vision system research has been carried out to improve image processing techniques using neural networks [9]. Spiking neural networks are considered as third generation of neural networks used for processing the biological information in brain [10].

Artificial neural networks are fairly old technique developed before fifty years. In progression the first generation of artificial neural networks consisted of McCulloch-Pitts threshold neurons, a conceptually very simple model: a neuron sends a binary 'high' signal if the sum of its weighted incoming signals greater than a threshold value. ANN of the second generation do not use a step- or threshold function to compute their output signals, but uses a continuous activation function, such as sigmoid and hyperbolic tangent. These types are feed-forward and recurrent neural networks. To give the appearance of real neuron, the third generation of neural network is developed that use spikes. Biological neurons use short and sudden increases in voltage to send information. These signals are more commonly known as action potentials, spikes or pulses. Here neurons encode information in the timing of single spikes, and not only just in their average firing frequency [13].

Spiking neural network is useful in real time processing which uses temporal coding scheme (like real neurons do) for improving processing speed and computational power [9]. So instead of using rate coding these neurons use pulse coding; mechanisms where neurons receive and do send out individual pulses, allowing multiplexing of information as frequency and amplitude of sound.

The important characteristic of SSN is to the information processed and encoded by the spikes. Various network models has been proposed for explain the visual system is able to image processing. The basic spiking neuron model for the visual cortex has been developed using Hodgkin and Huxley equation [11]. 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. This paper provides a comparative analysis to edge detection by using three methods.

II. THE CANNY EDGE DETECTOR

The Canny edge detector is widely used to be the standard edge detection algorithm in the industry, even though it is quit old. There is problem in edge detection such as signal processing optimization in other methods. To avoids this problem, canny edge detector is useful for approximate and optimize the edge searching problems. Firstly the Input image can be smoothen with a two dimensional Gaussian approximated by two one

dimensional Gaussians, one in the x direction and the another in the y direction. By taking the gradient of the image which changes in intensity, for indicating the presence of edges, which actually gives two results, the gradient in the x direction and the gradient in the y direction. Edges will detected at points the where the gradient is at a maximum. So, all points not at a maximum should be suppressed. For achieving this, the magnitude and direction of the gradient is calculated at each pixel. Then for every pixel check if the magnitude of the gradient is greater at one pixel's distance away in either the positive or the negative direction perpendicular to the gradient. If the pixel is not greater than both, suppress it. This gives non-maximal suppression. This method is known as hysteresis or edge thresholding. It provides use both a high threshold and a low threshold. If a pixel has a value greater than the high threshold, it is set as an edge pixel. If a pixel has a value greater than the low threshold and is the neighbor of an edge pixel, it is set as an edge pixel as well. If a pixel has a value greater than the low threshold but is not the neighbor of an edge pixel, it is not set as an edge pixel. If a pixel has a value below the low threshold, it is never set as an edge pixel [2].

III. ARTIFICIAL NEURAL NETWORK FOR EDGE DETECTION

We have to apply a lot of experiences to show the influence of sub-synapses, the step of training and parameter of learning in the process of learning using artificial neural networks and Spiking neural network.

A multilayer neural network was learning the canny operator. For validation and testing purpose, we used a series of image data base. We are using Berkeley data set for the edge detection purpose. This set is subdivided into two classes, one is for the network learning, and the other is for test of network generalization. Training of input layer is obtained by 3x3 masks sweeping the sample images. The network output is taken as the middle point in the image, resulting from the given data set [4]. Back propagation algorithm is applied for each image data base. This algorithm is used for finding the change in weights back propagating the obtained output to input. After testing the generalization procedure task, in each case, we design a distributed system for further processing. We calculate the error parameters for further application. Once, we have the different network error parameters for each set of images, we use them accordingly in forward operation. The main advantage of artificial neural network is that it gives less operation load as well as more advantageous for reducing the noise effect [5].

GENERAL ARCHITECTURE OF PULSE MODE NEURAL NETWORKS

The limitation of conventional algorithms is that multiple threshold values need to be set through a trial and error process, which affect the performance of these algorithms. To improve the performance of edge detection approach, artificial neural networks has been applied to edge detection. To achieve this, neural networks can be trained to detect edges and worked as non linear filter after fully trained. Multiple neural networks are trained by synthetic edge patterns, each one of them can detect a specific edge pattern.(e.g .vertical, horizontal, diagonal etc.)[6]. In this system every pixel of image used as input edges obtained are an output of neural network [7].

The operation of the Multilayer Neural Network is divided into two phases, learning phase and retrieving phase. During learning phase, weights are adjusted to perform a particular application to minimize the errors which affect the performance. During the retrieving phase, data from neurons of a lower layer is propagated forward to connection network [4]. Activation function which we are using is a sigmoid function which is use to generate the values between (0,1) for normalizing the values before applying to input and reduced between (0,1) [8].

The block diagram of architecture of edge detection operation is given in figure 1.in this, we provide Berkeley edge detection data set as a input. A test image is converted into binary format using MATLAB. Then the binary values are multiplied with that of the weight function and forwarded to that of the neuron unit the neuron unit provides the detected edges as output.

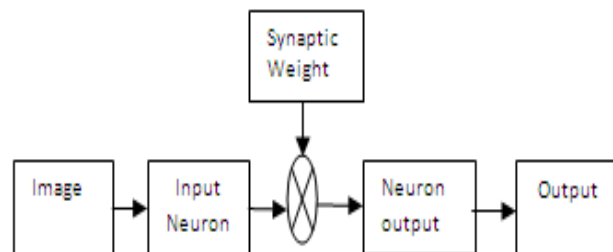


Figure 1. Architecture of the Edge detection operation with ANN

SPIKING NEURON MODEL

There are many different schemes for the use of spike timing in computation of information in neural network. A network based on spiking neurons is able to perform edge detection within a time interval of 100ms [9]. This processing time is consistent with the human visual system. The integrate-and-fire model, which is very commonly used in networks of spiking neurons. This model is easy to understand and implement. However, as it

approximates the very detailed Hodgkin-Huxley model very well it captures generic properties of neural activation of neurons.

The most widely used and well-known model of threshold fire Neurons, and spiking neurons is the integrate and-fire neuron. A spike travels down the axon and is transformed by a low-pass filter, which will convert the short pulse into a current pulse $I(t-t_j(f))$ which is used to charge the integrate-and-fire circuit. The resulting increase in voltage there can be seen as postsynaptic potential $\epsilon(t-t_j(f))$. Once the voltage over the capacitor goes above threshold value and the neuron sends out a pulse as illustrate in Figure 2 below.

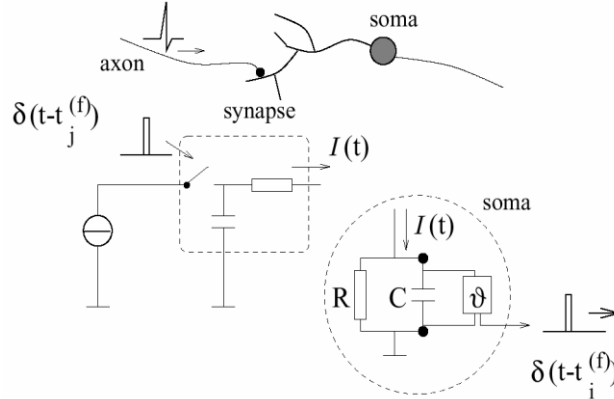


Figure 2. Schematic drawing of the integrate-and-fire neuron
Mathematically it can be explained as:

$$\tau_m \frac{du}{dt} = -u(t) + RI(t) \quad (1)$$

This equation describes the effects on membrane potential u over time. As the spike-response model the neuron fires once, u crosses threshold value and a short pulse δ is generated. To force a refractory period after firing we fix u to $K < 0$ for a period of δ .

$$I_i(t) = \sum_{j \in \mathcal{I}_i} c_{ij} \sum_{t_j^{(f)} \in \mathcal{F}_j} \delta(t - t_j^{(f)}) \quad (2)$$

The input current I for neuron i will set to be 0, as the incoming pulses have a finite short length. Once a spike arrives, it can be multiplied by synaptic efficacy factor c_{ij} forming the postsynaptic potential which charges the capacitor. This model is computationally simple [13]. The most widely acceptable spiking neuron model which was developed from Hodgkin and Huxley's work based on the obtained experimental recordings from number of experiments on the giant squid axon using a voltage clamp method. However, even though this model is biologically plausible. Due to the number of differential equations used by this model, the complexity in simulation is very high. Therefore, most computer simulations of neuron models preferred 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 review of the biological behavior of single neurons can be found in [13] and a comparison of different neuron models can be found in [14].

For implementation, the conductance-based I&F model has been chosen to model the network neurons in this work. This model provides an identical neuron behavior as that of Hodgkin-Huxley model for providing a reduction in computational complexity. In the conductance-based I&F model the membrane potential $u(t)$ is given by the following equation:

$$C_m \frac{du(t)}{dt} = g_l(E_l - u(t)) + \frac{w_{ex}g_{ex}}{A_{ex}}(E_{ex} - u(t)) + \frac{w_{ih}g_{ih}}{A_{ih}}(E_{ih} - u(t)) \quad (3)$$

where C_m is the membrane capacitance, E_l is the membrane reversal potential, g_l is the conductance of the membrane, E_{ex} and E_{ih} are the reversal potential of the excitatory and inhibitory synapses respectively, w_{ex} and w_{ih} are weights for excitatory and inhibitory synapses respectively, and A_{ex} and A_{ih} are the membrane surface area connected to the excitatory and inhibitory synapses respectively.

If the membrane potential $u(t)$ exceeds the threshold voltage v_{th} an action potential is generated and then $u(t)$ is reset to u_{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 $g_{ex}(t)$ and $g_{ih}(t)$ represent the conductance's of excitatory and inhibitory synapses respectively, which vary with time [13]. The output spike train is then provided by a series of 1s or 0s representing whether a neuron fires or not at time t , i.e.

$$[S_{out}(t_1), S_{out}(t_2), \dots, S_{out}(t_M)] \quad (4)$$

IV. SPIKING NNEURAL NETWORK STRUCTURE

Receptive field in biological system is the field where spiking neuron integrates the spikes from a group of afferent neurons as illustrated in Figure 3. Neuron N has a receptive field with a 6 neuron hexagonal array. Each neuron in the receptive field connects to neuron N through both excitatory and inhibitory synapses [11].

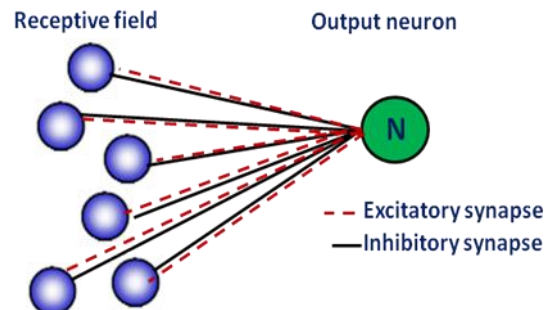


Figure 3. Receptive field of a spiking neuron.

The human vision system (HVS) [11] processes a visual scene starting in the retina where light intensity is converted into nerve signals within the photoreceptors. The system detects the edges in image effectively by using various receptive fields from simple cells in the visual cortex. These neurons can be simulated by basic spiking neuron model proposed by the Hodgkin and Huxley equation [9].

V. EXPERIMENTAL RESULTS AND EVOLUTION

We ran original image through our edge detectors. We have chosen the image defined in pixels of 512*512 pixels. Firstly test image was converted into grayscale using Matlabs RGB2GRAY function. Various threshold, sigma, slopes were arbitrary chosen. The image was blurred by a Gaussian filter before being applied to edge detection algorithm. Same steps are applying edge detection using artificial neural networks and Spiking neural network. We have to apply a lot of experiences to show the influence of sub-synapses, the step of training and parameter of learning in the process of learning using artificial neural networks and Spiking neural network.

To compare the results of canny edge detection with other models, we are used artificial neural networks and Spiking neural network. We record the Behavior of each output neuron which gives for each input pixel an output binary 1 if neuron is active otherwise 0 if the neuron is inactive. This gives result of binary matrices. The activation of output neurons can be represented by binary images after edge detection of these neurons of each class. Finally we combine all matrices to have the final edges by superimposing the resulting images.

The results are obtained from edge detection and a comparison with other methods is shown in fig 4.

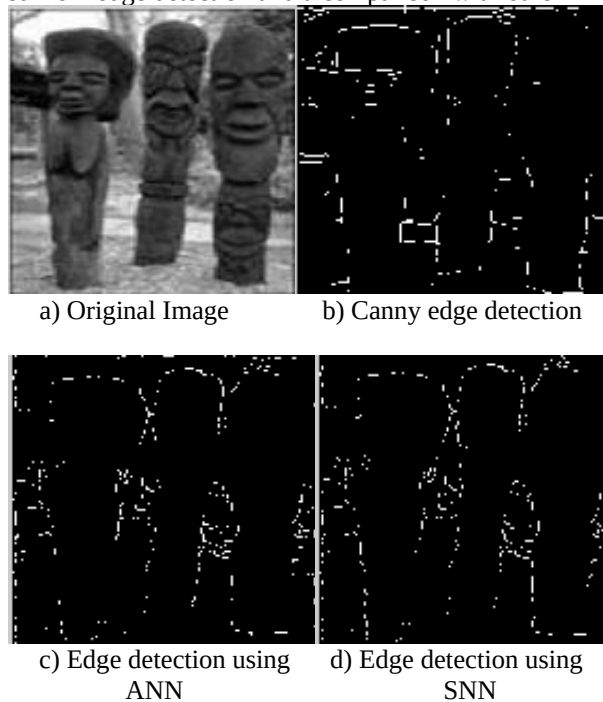


Fig. 4

The following table gives the error parameters obtained for resulting image.

Sr. No.	Edge Detection Technique	Processing Time(s)	MSE	PSNR
1	Canny	28.5	1.00	00.04dB
2	ANN	186.6	0.02	21.81dB
3	SNN	1.27	0.01	37.48dB

The results are obtained from edge detection and a comparison with other methods is shown in fig 5.

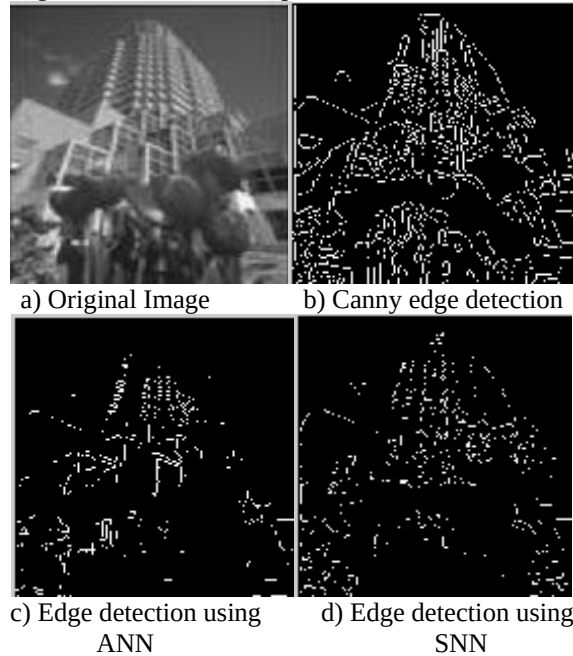


Fig. 5

The following table gives the error parameters obtained for resulting image.

Sr. No.	Edge Detection Technique	Processing Time(s)	MSE	PSNR
1	Canny	14.01	0.96	00.32dB
2	ANN	192.63	0.10	20.19dB
3	SNN	1.38	0.05	32.06dB

The results are obtained from edge detection and a comparison with other methods is shown in fig 5.

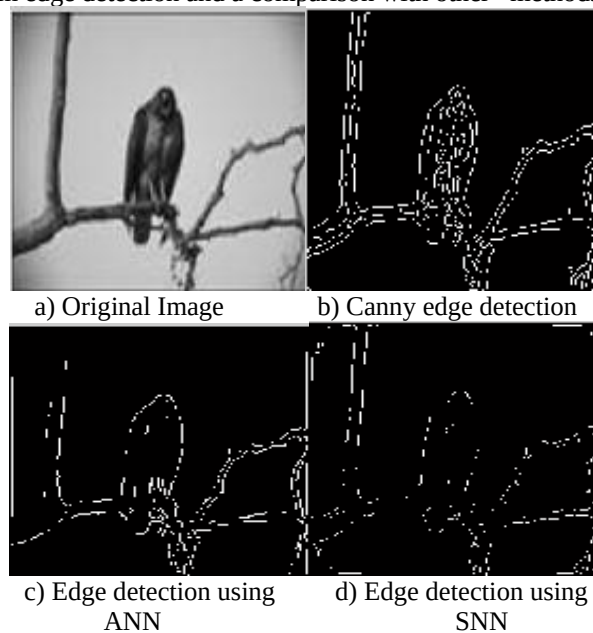


Fig. 6

The following table gives the error parameters obtained for resulting image.

Sr. No.	Edge Detection Technique	Processing Time(s)	MSE	PSNR
1	Canny	2,19	0.94	00.54dB
2	ANN	212.81	0.06	23.72dB
3	SNN	1.40	0.02	34.85dB

To see edge detection is closer to original image, an error metric is required. For this; the error between the original image and the quantized image is generally used. To evaluate the edge detection we had used error metrics to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is defining as the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$MSE = \frac{1}{MN} \left[\sum_{x=1}^M \sum_{y=1}^N [I(x,y) - I'(x,y)]^2 \right]$$

$$PSNR = 20 * \log_{10} [(255 / \sqrt{MSE})]$$

where $I(x,y)$ is the original image, $I'(x,y)$ is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a higher value of PSNR. Logically, value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, if you find a compression scheme having a low MSE (and a high PSNR), you can recognize that it is a better one. From the above table we would like to emphasize that the SNN method provides better results over the canny edge detection and artificial neural network. In this paper we focus on improving our performance parameters using spiking neural network.

VI. CONCLUSION

In this paper, we have applied a SNN model for image segmentation and edge detection. To use a SSN for both these problems, we have addressed the issue of parameter selection. We have focused our study on the key parameters: network architecture (number of sub synapses, receptive fields, output neurons) and learning parameters (training step, size of the training data base, peak of the learning function). These parameters are set up for each specific image problems. Results have shown that a careful setting of parameters is required to obtain efficient results. Future works will concern the application of this works to image sequences. Spiking neural networks are constructed by a hierarchical structure that is composed of spiking neurons with various receptive fields and plasticity synapses.

The spiking neuron models provide powerful functionality for integration of inputs and generation of spikes. Synapses are able to perform different computations, filters, adaptation and dynamic properties. Various receptive fields and hierarchical structures of spiking neurons enable a spiking neural network to perform very complicated computations, learning tasks and intelligent behaviors in the human brain. This paper demonstrated how a spiking neural network can detect edges in an image. Although the neuron circuits in the brain for edge detection are not very clear, the proposed network model is a possible solution based on spiking neurons. In the simulation, the neuron firing rate map for edges can be obtained with a less time interval. This time interval is consistent with the biological visual system.

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