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A SURVEY ON COLOR IMAGE SEGMENTATION THROUGH LEAKY INTEGRATE AND FIRE MODEL OF SPIKING NEURAL NETWORKS

CHINKI CHANDHOK
Department of Electronics and Communication Engineering, Priyadarshini Institute of Engineering and Technology, Nagpur, India, chinkichandhok@yahoo.com

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CHINKI CHANDHOK

Department of Electronics and Communication Engineering, Priyadarshini Institute of Engineering and Technology, Nagpur, India
Email:chinkichandhok@yahoo.com

Abstract—Neurological research shows that the biological neurons store information in the timing of spikes. Spiking neural networks are the third generation of neural networks which take into account the precise firing time of neurons for information encoding. In SNNs, computation is performed in the temporal (time related) domain and relies on the timings between spikes. The leaky integrate-and-fire neuron is probably the best-known example of a formal spiking neuron model. In this paper, we have simulated LIF model of SNN for performing the image segmentation using K-Means clustering. Clustering can be termed here as a grouping of similar images in the database. Clustering is done based on different attributes of an image such as size, color, texture etc. The purpose of clustering is to get meaningful result, effective storage and fast retrieval in various areas. Image segmentation is the first step and also one of the most critical tasks of image analysis .Because of its simplicity and efficiency, clustering approach is used for the segmentation of (textured) natural images. After the extraction of the image features using wavelet; the feature samples, handled as vectors, are grouped together in compact but well-separated clusters corresponding to each class of the image. Simulation results therefore demonstrate how SNN can be applied with efficacy in Image Segmentation.

Keywords- *Spiking Neural Network (SNN), Spike; Integrate and fire neuron, Segmentation, Clustering, K-Means Algorithm*

I. INTRODUCTION

Images are considered as one of the most important medium of conveying information. Understanding images and extracting the information from them such that the information can be used for other tasks is an important aspect of Machine learning. One of the first steps in direction of understanding images is to segment them and
find out different objects in them. Thus image segmentation plays a vital role towards conveying information that is represented by an image and also assists in understanding the image. Image segmentation is the process of dividing the given image into regions homogenous with respect to certain features, and which hopefully correspond to real objects in the actual scene. Segmentation plays a vital role to extract information from an image to create homogenous regions by classifying pixels into groups thus forming regions of similarity. The homogenous regions formed as a result of segmentation indwell pixels having similarity in each region according to a particular selection criteria e.g. Intensity, color etc. Our generic neuron [1] has four functionally distinct parts, called dendritic tree, soma, axon and synapse. Signals from other neurons are collected by the dendrites (input device) and are transmitted to the soma (central processing unit). If the total excitation caused by the input is sufficient, i.e., above threshold, an output signal (action potential or spike) is emitted and propagated along the axon (output device) and its branches to other neurons. The duration of an action potential is typically in the range of 1 to 2*ms* with an amplitude of about 100m*v*[2][17]. The integrate-and-fire neuron is perhaps the most used and well-known example of a formal spiking neuron model.
First proposed in the Hodgkin's/Huxley model in 1959[3]. The basic model is also called leaky-integrate-and-fire (LIF) because the membrane is assumed to be leaky due to ion channels, such that after a PSP the membrane potential approaches again a reset potential *urest*. This model is also known as the *linear* integrate-and-fire neuron. A network of leaky integrate-and-fire (LIF) neurons is being proposed to segment gray-scale images. This work aims to achieve simulation of a SNN model for image segmentation using K-means Clustering where K-Means method is numerical, unsupervised, non-deterministic and iterative in nature. A segmentation might be used for object recognition, image compression, image editing, etc. The quality of the segmentation depends upon the digital image. In the case of simple images the segmentation process is clear and effective due to small pixels variations, whereas in the case of complex images, the utility for subsequent processing becomes questionable.

II. SPIKING NEURAL NETWORKS

Spiking neural networks belong to the 3rd generation of neural networks and, like their biological counterparts, use spikes or pulses to represent information flow. Information is encoded both in the timing as well as the rate of spiking. The motivation behind exploring the spiking neuron models is that temporal information can also be encoded in the input signals and multiplexing can be achieved using pulse coding. Also, spiking ANNs are more biologically plausible than traditional ANNs Spiking neural networks (SNNs) are based on spiking neuron models and plasticity synapses. In general a spiking neuron operates by integrating spike responses from presynaptic neurons and generating an output spike when the membrane potential reaches a threshold value. Spiking Neuron Network (SNN) are often referred to as the 3rd generation of neural networks which have potential to solve problems related to biological stimuli.[4][18] They derive their strength and interest from an accurate modeling of synaptic interactions between neurons, taking into account the time of spike emission. SNNs model the precise time of the spikes fired by a neuron, as opposed to the conventional neural networks which model only the average firing rate of the neurons. The computational power of neural networks based on temporal coding [5] by spikes has been studied and proved that simple operations on phase-differences between spike-trains provide a powerful computational tool. For the last decade, SNNs have been successfully used in complex data processing problems solving, particularly in satellite image processing applications of Character Recognition/Pattern Recognition [17], Automatic Guided Vehicles (AGVs) etc. Spiking models have been applied in a wide range of areas from the field of computational neurosciences [20] such as: brain region modeling, auditory processing [21-22], visual processing [9-10], robotics [23-24] and so on. One commonly used unsupervised learning approach for spiking neural networks is called spike time dependent plasticity (STDP). It is a form of competitive Hebbian learning and uses spike timing information to set the synaptic weights. This is based on the experimental evidence that the time delay between pre- and post-synaptic spikes helps determine the strength of the synapse. . Spike time dependent plasticity (STDP) is used for training. [6,7] .

III. LIF MODEL OF SNN

The LIF model is one of the most widely used in computational neuroscience. One of the reasons for this is that it is the easiest to implement. The integrate-and-fire neuron [8] is perhaps the most used and well-known example of a formal spiking neuron model. The neuron is considered leaky if there is decay with a characteristic time constant in the summed contributions to the membrane potential; when this “leak” is forfeit the model is considered a perfect integrator. When an input current is applied, the membrane voltage increases with time until it reaches a constant threshold Vth, after which a spike occurs and the voltage is reset to its resting potential, after which the model continues to run. The firing frequency of the model thus increases linearly without bound as input current increases. The model can be made more accurate by introducing a parameter t_{ref} that limits the firing frequency of a neuron by preventing it from firing during that period. The absolute refractory period is followed by a phase of relative refractoriness where it is difficult, but not impossible to excite an action potential [19].

IV. IMPLEMENTATION OF LIF MODEL

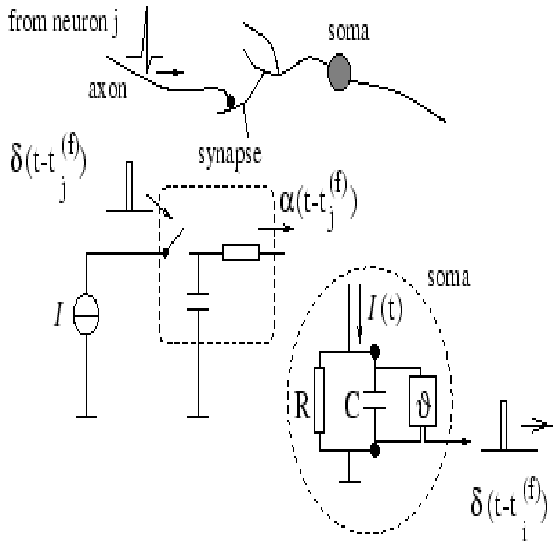


Figure 1 shows Schematic diagram of the Leaky integrate-and-fire model.

The basic circuit is the module inside the dashed circle on the right-hand side. A current I(t) charges the RC circuit. The voltage u(t) across the capacitance (points) is compared to a threshold . If u(t) = at time ti(f) an output pulse (t - ti(f)) is generated. Left part: A presynaptic spike (t - tj(f)) is low-pass filtered at the synapse and generates an input current pulse (t - tj(f)). The LIF model is implemented as follows

a) Defining Model of Neuron
The object of model of neurons in the network is to define Differential Equations (DEs) of the neuron behavior. It is necessary to define the spike detection (also known as threshold or event) and reset functions.

b) Defining Synapse Model
Synapse Model describes the process of interaction of neurons in the network with each other It also describes the effect of external spiking inputs on neurons.

c) Defining Adaptation Model
Adaptation model is used to describe the learning mechanisms available for a specific SNN. Synaptic weight, transmission delay, threshold value, and model parameters are defined using adaptation mechanism.

d) Defining Input/output of the Model
It is used to specify several features of input and output system of SNN such as which values external inputs have at any time for the simulation results and output spike times., Creation of SNN Model,

gathering together previous modules in a single SNN object.

e) Simulating SNN

SNN is simulated by specifying simulation parameters such as start and stop time, initial conditions, DE solver type, user defined custom function and stop function.

IV. IMAGE SEGMENTATION

Segmentation is the process of partitioning a digital image into multiple segments based on pixels. It is a critical and essential component of image analysis system. The main process is to represent the image in a clear way. The result of image segmentation is a collection of segments which combine to form the entire image. Real world image segmentation problems actually have multiple objectives such as minimize overall deviation, maximize connectivity, minimize the features or minimize the error rate of the classifier etc. Image segmentation is a multiple objective problem. It involves several processes such as pattern representation, feature selection, feature extraction and pattern proximity.

A large number of segmentation algorithms have been developed since the middle of 1960, and this number continually increases at a fast rate. Segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture [10][11].

V. CLUSTERING

Clustering is a process of organizing the objects into groups based on its attributes. A cluster is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters. An image can be grouped based on keyword (metadata) or its content (description). In keyword based clustering, a keyword is a form of font which describes about the image keyword of an image refers to its different features.

In this paper, the clustering process is performed by using a classical algorithm, such as K-Means. Clustering is a data mining technique used in statistical data analysis, data mining, pattern recognition, image analysis etc. Different clustering methods include hierarchical clustering which builds a hierarchy of clusters from individual elements. Because of its simplicity and efficiency, clustering approaches were one of the first techniques used for the segmentation of (textured) natural images [12].

In partitional clustering, the goal is to create one set of clusters that partitions the data in to similar groups. Other methods of clustering are distance based according to which if two or more objects belonging to the same cluster are close according to a given distance, then it is called distance based clustering. In probabilistic clustering, data is picked from mixture of probability distribution and we use the mean, variance of each distribution as parameters for cluster.

VII. CLUSTERING ALGORITHMS

An image may contain more than one object and to segment the image in line with object features to extract meaningful object has become a challenge to the researches in the field. Segmentation can be achieved through clustering. This paper critically reviews and summarizes different clustering techniques. There are various clustering algorithms each having its own significance depending upon their requirement in each application. Pillar k-means algorithm designates positions of initial centroids in the farthest accumulated distance between them in the data distribution .Using this approach, it is possible to reach the computational time as fast as k-means clustering and reach high quality of segmented results. In spatial constrained k-means algorithm, on each level of k-means clustering we perform region growing of those pixels belonging to the same feature cluster through a connected-components algorithm to produce a set of labeled image regions. Then the k-means algorithm on next level is carried out on these regions separately. The most popular method for image segmentation is k-means clustering [13][14]. Thus we have stable propagation of regions well matched with spatial constraints. During such process we achieve the image segmentation results in a coarse to fine manner hierarchically.

Fuzzy clustering algorithm updates the degree of membership in a fashion that minimizes the fuzzy within cluster variance. The clustering result is a list of membership degrees of the objects to all the clusters, this allows one to make his own decision, and even incorporate local approaches for the pixels that have weak membership degrees(edge pixels).It has the drawback of sensibility in a noisy environment. Heirarchical clustering algorithm is performed to the pixel image to obtain initial cluster centers.

The batch phase of Matlab based cluster algorithm is fast, but potentially only approximates a solution as a starting point for the second phase [15][16]. The second phase uses online updates, where points are individually reassigned if doing so will reduce the sum of distances, and cluster centroids are recomputed after each reassignment.

VIII. RESULTS

A. Results of Spike Generation

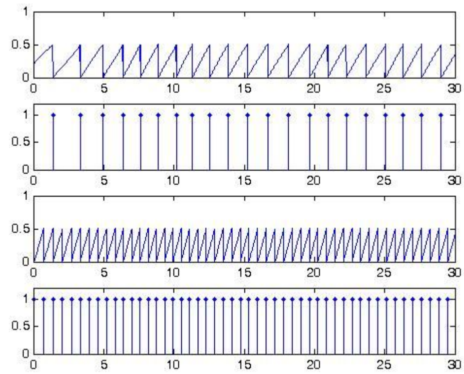


Figure2. State diagram and spike generation diagram for different neurons

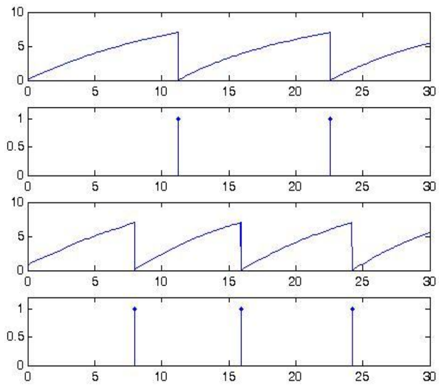


Figure3. State Diagram and spike diagram of First and Second Neuron Respectively

A. Image Segmentation Results with two different Images

a) Football.jpg

Figure 4.Original image

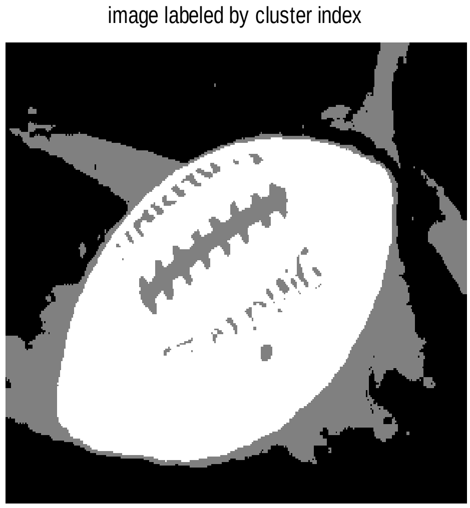


Figure5.Objects in cluster1

Figure6. Objects in cluster2

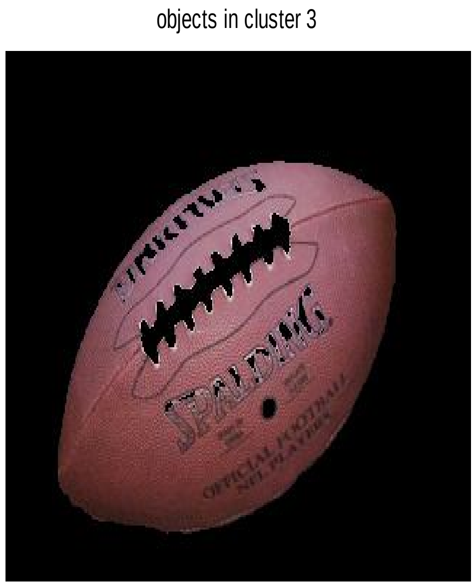
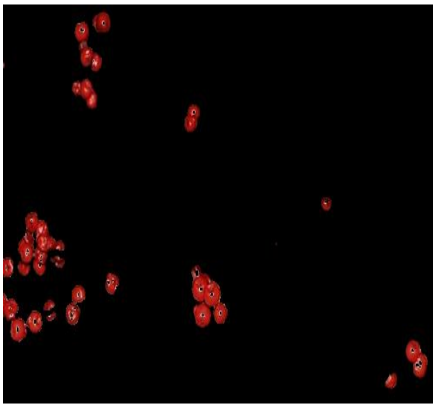


Figure 7.Objects in cluster3

b) greens.jpg

Figure8. Original image



Fiure9.Objects in cluster3

B. Segmentation Results of K-Means

Parameters	Image 1 football.jpg	Image2 greens.jpg
PSNR	13.0798	15.5175
MSE	17580.5	13777.3
MAE	111.312	91.22
NCD	1.44849	1.40405

CONCLUSION

We have successfully implemented Leaky Integrate and Fire Model of SNN using Biological Neural Network Toolbox. K-means clustering algorithm is applied to this model for performing image segmentation. It is found that for smaller values of k, the algorithm gives good results. For larger values of k, the segmentation is very coarse, many clusters appear in the images at discrete place. Here, wavelet decomposition has been used to perform clustering at increasingly finer levels of decomposition. Wavelet based clustering is unsupervised one and give good results for the effective feature extraction. It is not sensitive to noise and is only applicable to low dimensional data.

Artificial neural networks have been applied in a wide range of problems such as pattern recognition, forecasting, and intelligent control. Perhaps, among the most popular neural network models we could mention the feed-forward neural network trained with the back-propagation algorithm[25-26] .The computational cost of LIF model is low compared to the feed-forward network of ANN.

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