A Comprehensive Study on Image Segmentation Using Pulse-Coupled Neural Networks

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Abstract - Pulse-Coupled Neural Network (PCNN) operates as a matrix of neurons, each uniquely corresponding to a pixel in the image being processed. Unlike traditional neural networks, PCNN does not require any training, making it highly suitable for image segmentation tasks. However, the complexity of PCNN arises from its numerous parameters, making parameter selection a challenging endeavor. In this work, we introduce a simplified PCNN architecture that includes an automatic parameter determination method. This approach is specifically designed for binary image segmentation and has been tested on various images, yielding results with distinct and desirable features. The proposed network iterates only four times, enhancing its efficiency. During pre-processing, RGB images are converted to HSV color space, and the V component undergoes further processing. This component is first filtered using an averaging filter, followed by a sharpening filter. The parameters for the PCNN are then generated automatically, eliminating the need for manual selection and making the network highly suitable for real-time image processing. The performance of the proposed network has been verified through tests on a variety of images.

Key Words: Neural Networks, Pulse Coupled Neural Networks, Image Processing

1.INTRODUCTION

Eckhorn's neuronal model, originally developed by Eckhorn et al. to mimic the behavior of cortical neurons in cats , was later adapted by Johnson et al. for image processing applications, resulting in the Pulse-Coupled Neural Network (PCNN) [1-2]. The PCNN consists of a matrix of neurons, with each neuron corresponding uniquely to a pixel in the image being processed. Notably, the PCNN does not require any training. It operates through an iterative process, governed by the following set of equations [3]:

$$F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{k,l} w_{ij,k,l} Y_{ij}[n-1] + S_{ij} \quad ------(1)$$

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{k,l} m_{i,j,k} Y_{i,j}[n-1] \quad ------(2)$$

$$U_{ij}[n] = F_{i,j}[n]\left(1 + \beta L_{i,j}[n]\right) \quad ------(3)$$

$$Y_{i,j}[n] = \begin{cases} 1 & U_{i,j}[n] > T_{ij}[n] \\ 0 & \text{otherwise} \end{cases} \quad ------(4)$$

$$T_{ij}[n] = e^{-\alpha_T} T_{i,j}[n-1] + V_T Y_{ij}[n] \quad ----(5)$$

Here Sij is the input stimulus of the neuron. Sij is usually set to the normalized grey level of the image pixels in (i, j) position. $Fi,j\ [n]$ is the neuron's feedback input in (i, j), and $Li,j\ [n]$ is the linking item. $Uij[n]$ is called the internal activity of neuron. $Tij[n]$ is the dynamic threshold. $Yij[n]$ is the pulse output of the neuron; it can take the values of 0 and 1 only. Other terms are scalar constants. In 1999, Johnson et al. published a comprehensive survey of the PCNN, highlighting the applications of PCNN and different PCNN models [4].

The Pulse-Coupled Neural Network (PCNN) has demonstrated the capability to achieve perfect image segmentation under specific conditions, even when the intensity values of adjacent regions overlap [5]. However, the standard PCNN includes numerous parameters, making it complex and challenging to use for image segmentation tasks. To address this issue, Wang et al. proposed simplified PCNN architectures specifically designed for image segmentation [6].Chen et al. utilized image analysis techniques to automatically determine parameter values [7], while Thejaswi et al. employed adaptive techniques for the same purpose [8]. The "Simplified Parameters Model of PCNN and its Application to Image Segmentation" refers to a streamlined version of the Pulse-Coupled Neural Network (PCNN) that involves reducing the number of parameters involved in the network's operation. PCNN is a neural network model inspired by the behavior of neurons in the visual cortex of mammals, particularly cats [9]. It has been widely used for tasks like image segmentation, where the goal is to partition an image into meaningful regions. In this context, the "Simplified Parameters Model" refers to a modified version of the traditional PCNN that aims to make it easier to use and implement by reducing the complexity of parameter selection. This simplified model retains the essential characteristics and functionality of PCNN while offering a more straightforward approach to parameter configuration. The application of this simplified model to image segmentation involves utilizing it as a tool for partitioning images into distinct regions or objects based on their visual characteristics. By employing the simplified parameters model, researchers and practitioners aim to streamline the image segmentation process, potentially improving efficiency and accuracy while reducing computational complexity [10-12].

2. Methodology

In this methodology, the input RGB image is first converted to the HSV color space, focusing on the V component (Value), which represents the brightness. This extracted V component is then subjected to a series of preprocessing steps to compute the required parameters for further processing. Once these parameters are determined, the preprocessed V component is fed into the Pulse-Coupled Neural Network (PCNN). The PCNN processes the input iteratively, ultimately producing the desired binary image segmentation. This approach ensures that only the brightness information is utilized, enhancing the effectiveness of the image segmentation. Figure 1 shows the process flow of this method. Figure 2 shows the diagram of a neuron of the proposed network.

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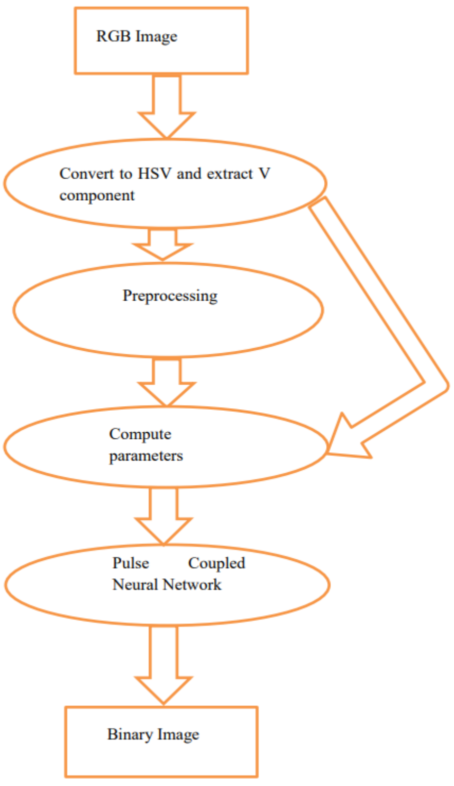


Fig-1 : Flow Diagram

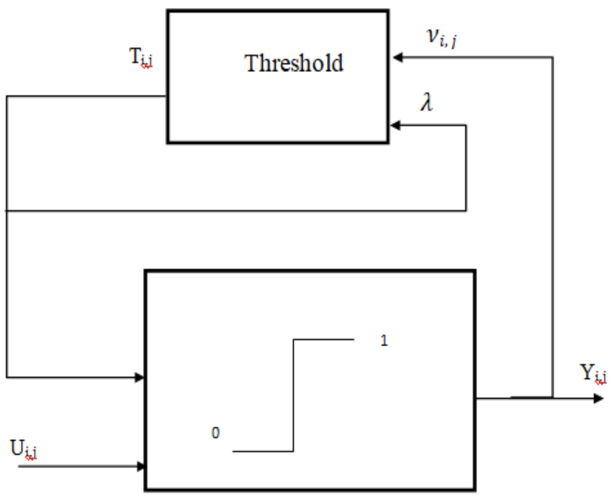


Fig-2 : Neuron of the proposed network

2.1. ALGORITHM DESCRIPTION

The input image is converted to the HSV color space, and the V component (Value) is extracted, as only the brightness is of interest in this context. The equations for the RGB to HSV transformation are as follows:

$$V = M_1$$

$$S = \frac{d}{M}, M > 0_i$$

$$H = 60 \times \begin{cases} \frac{a-b}{d}, M = r_1 \\ \frac{b-r}{a} + 2, M = g \\ \frac{r-g}{a} + 4, M = b. \end{cases}$$

Here

$$M = \max(r, g, b)$$
$$m = min(r, g, b)$$
$$d = M - m$$

The V component is the maximum value of the RGB components. The V component is then smoothed with an averaging filter of size 3x3, followed by convolving with the below kernel.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

This kernel acts a sharpening filter. Next the linear attenuation parameter (lambda) of the PCNN is computed as follows: if the normalized value of the Otsu's threshold of the V component of the image is greater than 0.6, then lambda is set to 0.1, else it is set to 0.055. The contrast of the processed V component of the image is then enhanced using the Contrast Limited Adaptive Histogram Equalization technique [17] with the clipping limit set to 2 and the grid size of the tile is set to 3x3. The processed V component of the image is then normalized. An intermediate parameter, β is calculated according to the method mentioned in [6]:

$$\beta_{i,j} = \frac{1}{\sqrt{STD_{ij}}+1}$$

Here STD_{ij} is the standard deviation of the grey value of the 8-connected pixels of the i th row, j th column pixel. From this parameter, ν parameter is calculated using this equation:

$$v_{i,j} = 1 + 6 * \beta_{i,j}$$

The normalized and pre-processed image is then fed to the internal activity, U of the PCNN. The PCNN is an iterative process. From experiments, it was found that it is suitable to set the iteration limit as 4. At each iteration, the output value of the PCNN, Y is obtained using the below equations:

$$Y_{i,j} = 1 \text{ if } U_{i,j} > T_{i,j}, \text{ else } 0$$

$$T_{i,j} = \lambda * T_{i,j} + v_{i,j} * Y_{i,j}$$

From the above equations it can be concluded that the proposed PCNN is of non-linking type since the input does not depend on neighbouring neurons.

3. SOFTWARE SIMULATIONS

The proposed Pulse-Coupled Neural Network (PCNN) was implemented using Python 3, an interpreted programming language known for its versatility and wide range of libraries. Specifically, the implementation utilized Python libraries such as os, glob, numpy, scipy, the Python Imaging Library, and opencv. The software simulations were executed on a desktop computer running the KDE Neon Operating System, which is based on Ubuntu. The desktop was equipped with an Intel i3-3220 processor operating at 3.30 ghz and 8 GB of RAM, providing a robust platform for processing. For image segmentation and boundary detection research, the Berkeley Segmentation Dataset was employed, as it is a widely recognized benchmark in the field. The input images were in JPG format, while the output images, processed to binary format with 1 bit per pixel, were stored in PNG format due to its support for binary images.

4. METHODOLOGY USED FOR SURVEY

Mean Opinion Score (MOS) is the method used in this project survey. MOS is a commonly used measure for video, audio, and image quality evaluation. MOS is obtained by taking the response of the observers to rate images for their quality on a particular scale such as a scale from 1 to 5 where 1 is bad and 5 is excellent.

Table 1. Mean Opinion Score rating

5	Excellent
4	Good
3	Fair
2	Poor
1	Bad

The MOS is calculated as the arithmetic mean

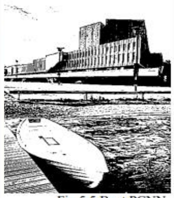
$$\text{MOS} = \frac{\sum_{n=1}^{N} Rn}{N}$$

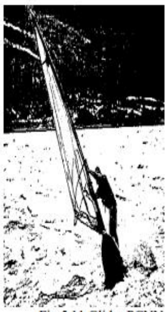
Where R are the individual ratings for a given stimulus by N subjects. For this survey total number of 32 responses have taken for 10 images through a google Forms. Using that the average rating of the images of proposed PCNN algorithm and Otsu's algorithm was calculated by the method of Mean Opinion square.

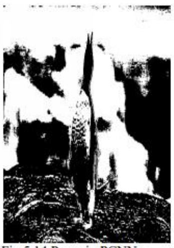
5. RESULTS AND DISCUSSIONS

In the results, the average ratings of binary images generated by the proposed Pulse-Coupled Neural Network (PCNN) and Otsu's method are compared on a scale of 5. The average rating serves as a quantitative measure of the quality or effectiveness of the segmentation results obtained from each method. According to the findings, the binary images produced by the proposed PCNN method received an average rating of 4.13447 out of 5. This suggests that, on average, the segmentation results achieved by the proposed PCNN approach were highly satisfactory, with the majority of objects and boundaries accurately delineated. In contrast, Otsu's method yielded binary images with a lower average rating of 2.76189 out of 5. This indicates that, on average, the segmentation results obtained using Otsu's method were less accurate or satisfactory compared to those generated by the proposed PCNN approach. These findings underscore the superior performance of the proposed PCNN method in terms of image segmentation quality, as evidenced by its higher average rating compared to Otsu's method. This difference in average ratings highlights the effectiveness of the PCNN approach in producing high-quality binary images suitable for various applications, such as object detection, classification, and analysis.

Table 1. Summary of results

Color Image	PCNN Image	Otsu's Image	Average of the PCNN Image	Average of the Otsu's Image
 Fig 5.1 Vase	 Fig 5.2 Vase PCNN	 Fig 5.3Vase Otsu	3.78125	2.55
 Fig 5.4 Boat	 Fig 5.5 Boat PCNN	 Fig 5.6 Boat Otsu	4.03125	2.84375

Color Image	PCNN Image	Otsu's Image	Average of the PCNN Image	Average of the Otsu's Image
 Fig 5.7 Man's Poster	 Fig 5.8 Man's Poster PCNN	 Fig 5.9 Man's Poster Otsu	4.3125	3.4375
 Fig 5.10 Glider	 Fig 5.11 Glider PCNN	 Fig 5.12 Glider Otsu	4.15625	2.9375

Color Image	PCNN Image	Otsu's Image	Average of the PCNN Image	Average of the Otsu's Image
 Fig 5.13 Penguin	 Fig 5.14 Penguin PCNN	 Fig 5.15 Penguin Otsu	3.875	2.4375
 Fig 5.16 Tribal Men	 Fig 5.17 Tribal Men PCNN	 Fig 5.18 Tribal Men Otsu	4.15625	2.3125

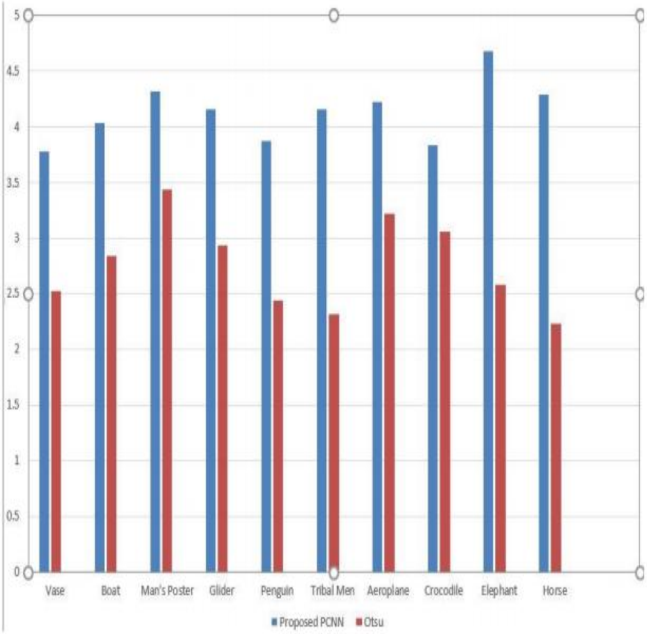


Fig 3: Graph of the responses for images of Proposed PCNN algorithm and Otsus algorithm

The resulting images exhibit a remarkable preservation of details from the original images, with most objects being readily identifiable. This observation underscores the effectiveness of the proposed network across a diverse range of image types, facilitated by the comprehensive nature of the utilized dataset encompassing various categories. Notably, the network's efficiency is highlighted by its completion within just four iterations, minimizing computational time without compromising accuracy. However, it's essential to note that computational requirements escalate exponentially with image size. A notable advantage of the proposed network is its autonomy from manual parameter selection, a feature reinforced by the consistent performance across diverse image types. This underscores the generalizability of the parameter estimation technique employed, further bolstering the network's applicability and reliability across different image contexts. Figure 3 shows the responses of the image of proposed PCNN and Otsu's algorithm.

5. CONCLUSION AND FUTURE SCOPE

The experimental findings affirm the versatility of the proposed network, showcasing its efficacy across diverse image types. With the PCNN algorithm completing in just four iterations, the hardware demands are modest, particularly for smaller images, rendering it conducive for resource-efficient processing. Moreover, the absence of manual parameter selection renders the network well-suited for real-time applications. Future research avenues may explore enhancing result image quality through refined preprocessing techniques. Given the algorithm's swift convergence and parameter-independent nature, avenues for its implementation in FPGA or ASIC architectures warrant investigation, particularly for real-time applications. Additionally, the potential integration of this algorithm with binarized neural networks, prevalent in literature for tasks like image classification and object detection, presents a compelling avenue for further exploration and advancement.

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