



## **EYES DETECTION IMPROVEMENT BY TRADITIONAL AND MODIFIED PULSE COUPLED NEURAL NETWORK**

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### **Abstract**

This paper presents a fast method and robust for eyes detection, using Traditional and Modified Pulse Coupled Neural Networks (MPCNN). The functionality of MPCNN is not the same as Traditional Pulse Coupled Neural Networks (TPCNN) because we are taking care about human visual perception not only the neighbor pixel characteristic. Due of this feature, the algorithm response time is around two milliseconds. The approach has two components including: face area detection based on segmentation and eyes detection using edge. Segmentation operation is ensured by MPCNN and edge detection by TPCNN.

The biggest region which is constituted by pixel value one will be the human face area. The segmented face zone which will be the input of TPCNN for edge detection undergoes a vertical gradient operation. The two gravity's center of close edge near the horizontal line which corresponds to the peak value of horizontal projection of vertical gradient image will be the eyes.

**Keywords:** Traditional Pulse Coupled Neural Network, Modified Pulse Coupled Neural Network, Face detection, Eyes detection, Image Segmentation, Edge Detection.

### **Introduction**

In recent decades, image processing domain has an exponential evolution. The current status is completely different from initial state. Actually, image processing





searches are oriented to object recognition especially for face recognition. Eyes detection is an important phase ensuring a good performance of face recognition. In this paper, an eyes detection approach will be proposed. The method is based on traditional and modified pulse coupled neural networks. It is divided in two parts: face detection first, following by eyes detection.

We will see in the next paragraph the traditional and modified pulse coupled neural networks, then the details of the proposed algorithm followed by the test phase, its performance measurement and its prospect.

### Traditional Pulse Coupled Neural Networks Model

The architecture of a Traditional Pulse Coupled Neural Networks (TPCNN) is rather simpler than most other neural network implementations. PCNN do not have multiple layers and receive input directly from the original image, forming a resulting “pulse” image. The network consists of multiple nodes coupled together with their neighbors within a definite distance, forming a grid (2Dvector). The TPCNN neuron has two input compartments: linking and feeding. The feeding compartment receives both an external and a local stimulus, whereas the linking compartment only receives a local stimulus. When the internal activity becomes larger than an internal threshold, the neuron fires and the threshold sharply increases. Afterward, it begins to decay until once again the internal activity becomes larger.

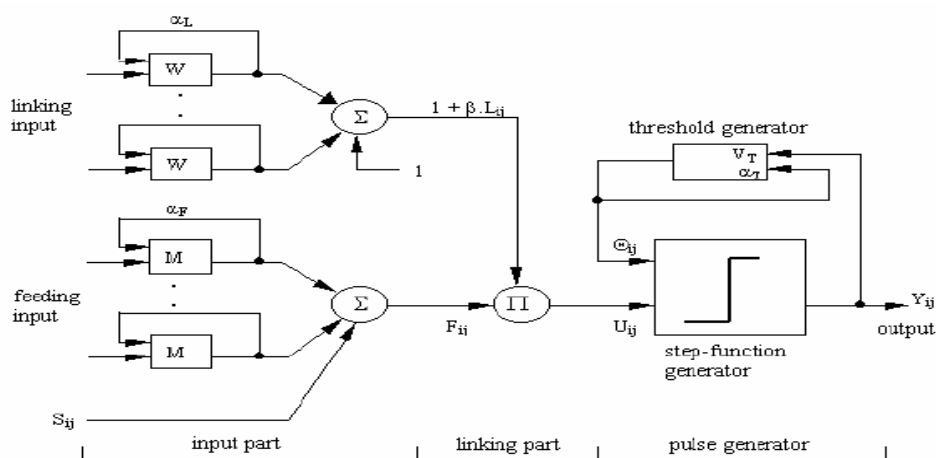


Fig. 1 Pulse Coupled Neural Networks Structure



This process gives rise to the pulsing nature of TPCNN, forming a wave signature which is invariant to rotation, scale and shift or skew of an object within the image. This last feature makes TPCNN a suitable approach for feature extraction in very-high resolution imagery, where the view angle of the sensor may play an important role. TPCNN system can be defined by the following expression:

$$F_{ij}(n) = S_{ij} + F_{ij}(n - 1) \cdot e^{-\alpha_F} + V_F \cdot (M * Y(n - 1))_{ij} \quad (1)$$

$$L_{ij}(n) = L_{ij}(n - 1) \cdot e^{-\alpha_L} + V_L \cdot (W * Y(n - 1))_{ij} \quad (2)$$

Where  $S_{ij}$  is the input stimulus to the neuron  $(i, j)$ ,  $F_{ij}$  and  $L_{ij}$  are respectively the values of the Feeding and Linking compartment. Each of these neurons communicates with neighboring neurons  $(k, l)$  by means of the weights given by  $M$  and  $W$  kernels.  $Y$  is the output of a neuron from the previous iteration, while  $V_F$  and  $V_L$  indicate normalizing constants. The output of feeding and linking compartment are combined to create the internal state of the neuron  $U$ :

$$U_{ij}(n) = F_{ij}(n) \cdot (1 + \beta \cdot L_{ij}(n)) \quad (3)$$

A dynamic threshold  $\Theta$ , is also calculated as follow:

$$\Theta_{ij}(n) = \Theta_{ij}(n - 1) \cdot e^{-\alpha_\Theta} + V_\Theta \cdot Y_{ij}(n - 1) \quad (4)$$

In the end, the internal activity is compared with  $\Theta$  to produce the output  $Y$ , by:

$$Y_{ij}(n) = \begin{cases} 1, & \text{si } U_{ij}(n) > \Theta_{ij}(n) \\ 0, & \text{sinon} \end{cases} \quad (5)$$

The result of a TPCNN processing depends on many parameters. For instance, the linking strength,  $\beta$ , affects segmentation and, together with  $M$  and  $W$ , scales feeding and linking inputs, while the normalizing constants scale the internal



signals. Moreover, the dimension of the convolution kernel affects the propagation speed of the autowave. With the aim of developing an edge detecting TPCNN, many tests have been made changing each parameter [1][3].

### Modified Pulse Coupled Neural Network Model

This model is deduced from traditional PCNN by introducing the luminance weight factor of human eyes. The equation (6) presents its formula:

$$KL_{ij} = \begin{cases} 2 - 0.0133F_{ij}, & F_{ij} < 75 \\ 0.0108F_{ij} - 0.3462, & F_{ij} > 125 \\ 1 & \text{other} \end{cases} \quad (6)$$

All TPCNN formula above were changed as below:

$$F_{ij}[n] = S_{ij} \quad (7)$$

$$L_{ij}[n] = V_L \sum_{kl} KL_{ij} Y_{kl}[n - 1] \quad (8)$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]) \quad (9)$$

$$Y_{ij}[n] = \begin{cases} 1, & U_{ij}[n] > \theta_{ij}[n - 1] \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

$$\theta_{ij}[n] = e^{-\alpha\theta} \theta_{ij}[n - 1] \quad (11)$$



Internally, we calculate the cross entropy of each output and the smaller value represents the image segmented. It means that we must choose the number maximum of iteration.

### Proposed Method

The method doesn't depend on image input format. In case of image color, the conversion to grayscale type is required. We have two steps to follow: face detection, then eyes detection.

The following figure presents shortly the chart of our algorithm.

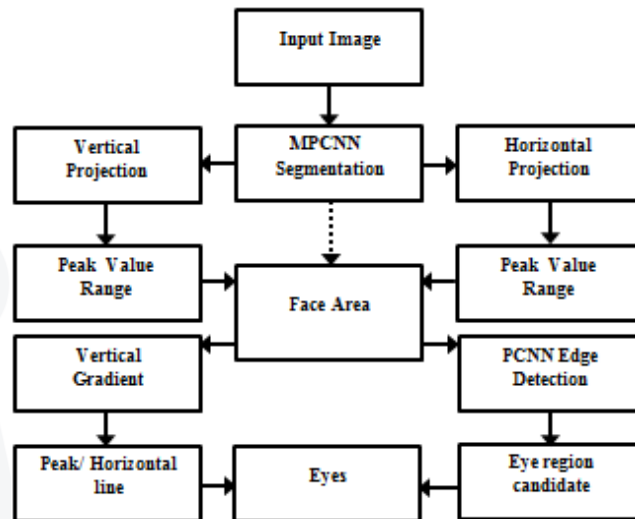


Fig. 2 Face/Eyes detection method

### Face detection

Searching face area focuses on the skin detection because it is the dominant part in the top portion of human image. Once we get grayscale image as input, we proceed to configure the MPCNN using the below parameters:

Set large number of iterations  $N_{\max} = 10$

Set static parameters:  $V_L = 0.2$ ,  $\beta = 0.1$ ,  $\alpha_\theta = 0.2$



Fig. 3 Original image



Fig. 4 MPCNN output

Once the original image with  $R \times C$  size is segmented, we calculate the sum of pixel value per row  $I_{pv_x}$  and per column  $I_{ph_y}$ .

$$I_{pv_x} = \sum_{x=1}^C I(x, y) \tag{12}$$

$$I_{ph_y} = \sum_{y=1}^R I(x, y) \tag{13}$$

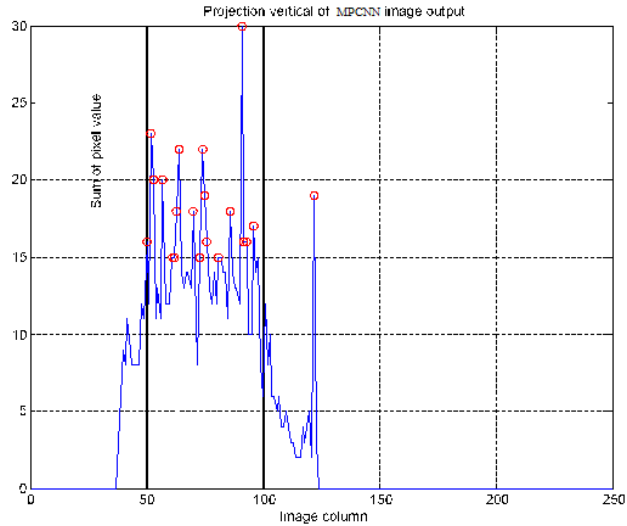


Fig. 5 Vertical projection of Fig. 4

The vertical projection graph presents some peaks values in the column range  $[x_1, x_2]$ , same case for horizontal projections in row range  $[y_1, y_2]$

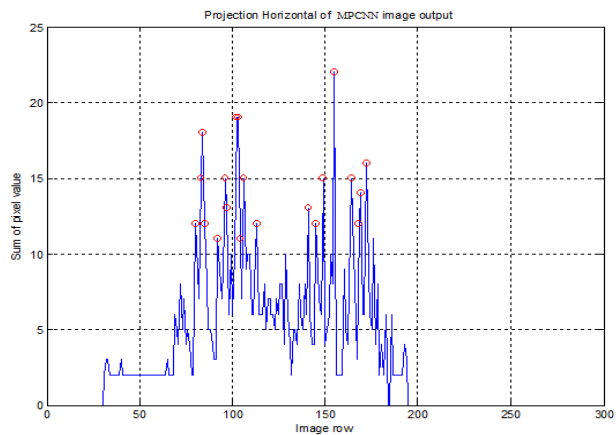


Fig. 6 Horizontal projection of Fig. 4

Face area is the intersection region of the two bands; it means the rectangle's area described on Fig. 7.

$$\text{Face area} = (x_2 - x_1)(y_2 - y_1) \quad (14)$$

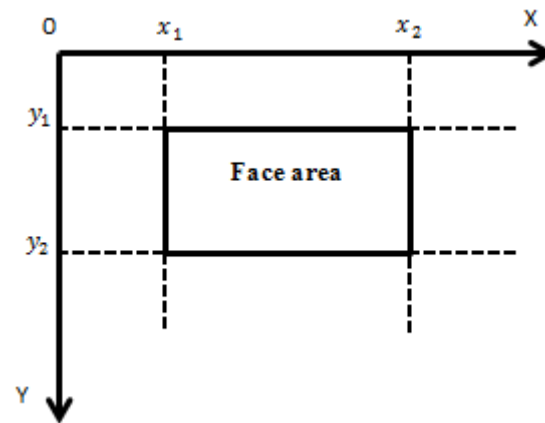


Fig. 7 Face detection method

With our experimental image:

$$x_1 = 33.5, x_2 = 127.5$$

$$y_1 = 26.51, y_2 = 87.5$$

And we get the following picture:

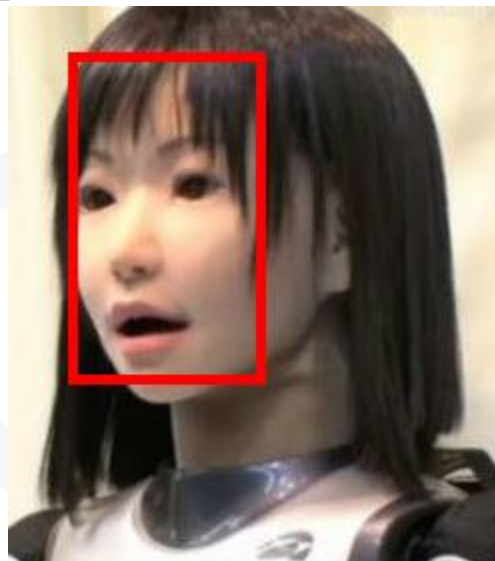


Fig. 8 Face area





### Eyes detection

After detecting the face, the next step is to localize the iris. We need to extract first the content of rectangle from the image segmented MPCNN's output (Fig. 4). Then, we customize each region to be delimited as well. The operation doing this task is available with Matlab called "imclose". The Fig. 9 presents the result of this operation.



Fig. 9 Region customization

The image with region closed becomes the input of traditional PCNN for edge detection. The Pulse Coupled Neural Networks will use the following parameters:

Weights matrix

$$M = W = \begin{bmatrix} \sqrt{2}/2 & 1 & \sqrt{2}/2 \\ 1 & 1 & 1 \\ \sqrt{2}/2 & 1 & \sqrt{2}/2 \end{bmatrix} \quad (15)$$

Initial values of matrix :

The initial values of linking L, feeding F matrix and stimulus S are the same as the input image. The convolution between null matrix which has the same size as the input image RxC and weights matrix initiates the output value Y of PCNN. The first value of dynamic threshold  $\theta$  is an R-by-C matrix of two.

Delay constants:

$$\alpha_F = 0.1, \alpha_L = 0.3 \text{ and } \alpha_\theta = 0.2$$



Normalizing constants:

$$V_F = 1.5, V_L = 0.2, V_\Theta = 20 \text{ and} \\ \beta = 0.1$$

The PCNN is ready for iteration exercise. two iterations are enough to get a good result of edge detection and the below figure show the output of final iteration.



Fig. 10 Third iteration

The M/PCNN have played two important roles: segmentation and edge detection. The closed edge will be filled with blank color (“imfill” Matlab function) and we calculate the difference between this one with the image of the last iteration of the PCNN.

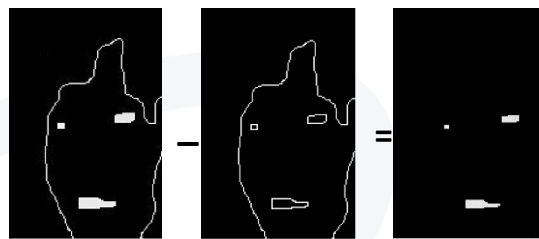


Fig. 11 Eyes regions candidates

Eye regions candidates are found, then we are looking for gravity's center of each region. For a 2D continuous domain, knowing the characteristic function  $f$  of a region, the raw moment of order  $(m + n)$  is defined as:

$$M_{mn} = \iint x^m y^n f(x, y) dx dy \quad (16)$$

For  $m, n = 0, 1, 2 \dots$  adapting this to scalar (greyscale) image with pixel intensities  $I(x, y)$ , raw image moments  $M_{mn}$  are calculated by:



$$M_{mn} = \sum_{x=1}^C \sum_{y=1}^R x^m y^n I(x, y) \quad (17)$$

The two raw moments order one  $M_{01}$  et  $M_{10}$ , associated with moment order zero  $M_{00}$  are used to calculate the centroid of each region. Its position is defined as:

$$X_g = \frac{M_{10}}{M_{00}} \text{ et } Y_g = \frac{M_{01}}{M_{00}} \quad (18)$$

Now, our problem is « how to identify the eyes? ». To answer this question, we proceed to calculate vertical gradient of face area segmented image.

$$\vec{G} = \overrightarrow{\nabla I_{\text{seg}}} = \begin{bmatrix} \frac{\partial I_{\text{seg}}}{\partial x} \\ \frac{\partial I_{\text{seg}}}{\partial y} \end{bmatrix} \quad (19)$$



Fig. 12 Vertical gradient of face area segmented

We use the same principle as the face detection by calculating the sum of gray level of vertical gradient image per row [2]. We get the peaks and draw the line (d) horizontal corresponding.

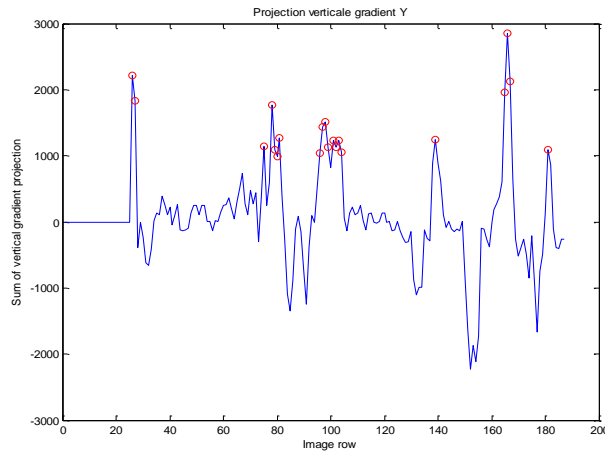


Fig. 13 Horizontal projection of Fig. 16

$$(d): y = p \quad (20)$$

(d) is the line carrier relevant information in top part of image and the two centers of gravity of a region near the horizontal line are the eyes. The distance between (d) and the center of gravity is calculated by:

$$d(C, (d)) = |Y_g - p| \quad (21)$$

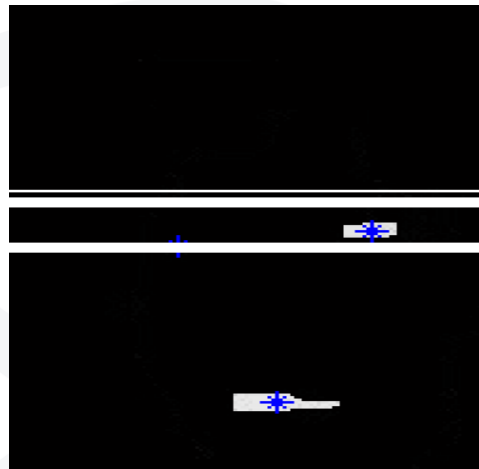


Fig. 14 Line and gravity's centers positions



Finally, the eyes are detected with more precision.

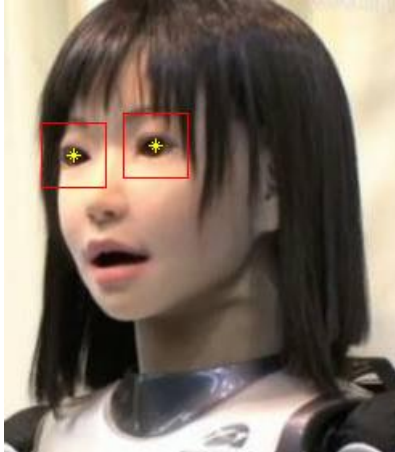


Fig. 15 Eyes detected

### Results and Performance

All tests were performed with image color with different dimension. As we know, the algorithm doesn't use a database image for training, so the eyes detection is very fast. However, it has a weakness when the person wears glasses because the iris is not detected correctly. Samples of the experimental results are shown in the series of pictures (Fig. 16 and Fig. 17) below:



Fig. 16 Multiple detection



Fig. 17 Testing results

An approximate measure of performance was done by passing image database test used by the methods listed on Table 2 and some image from internet, as input of our algorithm. The following table (Table 1) shows the result of testing:

Table 1: Performance measurement

	Face Detection	Eyes Detection
With glasses	99.81%	99.73%
Without glasses	99.83%	99.81%
Total	99.82%	99.77%

With performance 99.77%, we can say that our method is powerful. A comparison with another algorithm was done and the table (Table 2) indicates the results. We can use this algorithm for face recognition or reading facial expression.



Table 2: Comparison results

No.	Methods	Eyes detection rate success
1	Improved Proposed Method	99.7%
2	Choi and Kim [4]	98.7 %
3	Previous Proposed Method [10]	98.5%
4	S. Asteriadis, N. Nikolaidis, A. Hajdu, I. Pitas [5]	98.2%
5	Song and Liu [6]	97.6 %
6	Kawaguchi and Rison [7]	96.8 %
7	Eye detection based-on Haarcascade classifier	96.5%
8	Zhou and Geng [8]	95.9 %

## Conclusions

In this paper, we proposed a method for eyes detection using traditional and modified Pulse Coupled Neural Networks which were inspired by the human visual cortex. The algorithm has two parts: face detection which is based on segmentation and eyes detection based on edge detection. The method is very fast due of iteration instead of image database learning. The time requirement of the algorithm is two millisecond which is acceptable for real time applications and less than this with grayscale image. The success rate is up to 99.73% for a picture with a person without glasses against 99.81% with glasses.

Our prospects are turning to extract face feature such as nose and mouth.  $E_1(X_{g1}, Y_{g1})$  And  $E_2(X_{g2}, Y_{g2})$  are the iris position. ( $\Delta$ ) Which is perpendicular line with  $[E_1E_2]$  segment, passes in middle of the both irises. The first black region from MPCNN output passed by ( $\Delta$ ) is the noise and the mouth is the second one.

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