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# Pulse Coupled Neural Network for Identifying the Tuberculosis on Human Lung

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**Synopsis**

Pulse Coupled Neural Network (PCNN) is an appropriate tool for image processing and pattern recognition. The advantage of PCNN is needless pre-processing of the image that will be identified. PCNN is not influenced by rotation, translation, and distortion of the image, thus the method can be considerated as human lung tuberculosis identification method through rontgent (X-ray) results image based. This paper explores the performance testing for PCNN method compared to the classical standard method for tuberculosis detection. There is significant improvement for processing time, and diagnosis percentage, which the image is processed first with Adaptive White Gaussian Noise (AWGN) for reliability testing of the method.

KEYWORDS: Pulse coupled neural networks, medical imaging, tuberculosis, human lung

## 1. Introduction

One of the most important and difficult tasks the radiologist has to carry out consists of detection and diagnosis of tuberculosis infected lung regions from medical images. Some of these regions may not be detected due to the fact that they may be camouflaged by the underlying anatomical structure, or the low quality of the images or the subjective and variable decision criteria used by radiologists.
Therefore, for the automatic detection of tuberculosis level, it is necessary to develop a computer-aided diagnosis support system using image processing and intelligent computing, which can help radiologists to diagnose the level of tuberculosis [1)]. There are numerous of image identification methods, which have been developed for diagnosis needs. The neural network method, like Backpropagation with its error-iterative method and Kohonen with its Self Organizing Method (SOM) are useful, however, those methods need long pre-processing time and big resource. Beside that, for those Neural Network methods is required many and complicated weights and parameter updating for larger image input [1,3)]. To improve the weakness as mentioned above, PCNN is implemented for pre-processing of image recognition.
Eckhorn has pioneering the development of the *Pulse Coupled Neural Network (PCNN)* method in 1990 based on biologically inspired algorithm. PCNN recently become fashionable for image processing, thus, in this paper the PCNN for performing image segmentation in the realm of medical diagnostics is discussed. Successfully work for using PCNN is reported [2)], this work have been done for classifying breast cancer from the ultrasound image data. PCNNs were tested with X-ray image result of human lung, abnormalities of image caused by tuberculosis diseases is attempted for identifying.
The fundamental of PCNN is *Linking Field Neural Network* spurred by the experimental observations of synchronous pulse bursts in the cat visual cortex and addressed for signal or image pre-processing application which is the group of procedures for contour detection and especially for image segmentation. The pixels of the image are processed in such a way that the network takes a couple of pixels at the same time, and detects dissimilarities in this region of pixels. This method is extremely helpful for segmentation of images. Some works for implementing the PCNN in image recognition has proposed, and successfully results are presented [4,5,6)].
In this article, PCNN concentrate on the segmentation of human lung images. PCNN is as an exclusive neural network technique to detect dissimilar regions in an image, which is called region of interest (ROI) or suspected regions. Furthermore, this method will be used for separating the human lung image in segments of dissimilar image that is caused by tuberculosis diseases. Thus, will help the phycisian for identifying early, and exact diagnose.

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## 2. PCNN (Pulse Coupled Neural Network) Algorithm

In this paper, PCNN is the key of the whole developed system. PCNN as a neural analyzer that is made of pulse coupled neurons, where perform similar to local analyzer cells. The pulsates generated by the neurons is a straight outcome of incentive excitation and lateral connection among neurons. Lateral connection/ interaction and advance
stimulation decides the neurons to fire in synchrony in the homogenous areas related to the image. These properties can be exploited in image segmentation. However, is assumed that the pulsates of the neurons captures somehow morphological information from the image.
The model that is proposed by T. Lindblad, and J.M. Kinser is used to perform the network. The pulse-coupled neuron is a specific form of leaky integrator neuron [5)], and the exponential terms in equations (1) and (2) are the leaky integrator model. By increasing the threshold when the neuron fires and decreasing it exponentially after firing are performing the simulation of the refractory period.

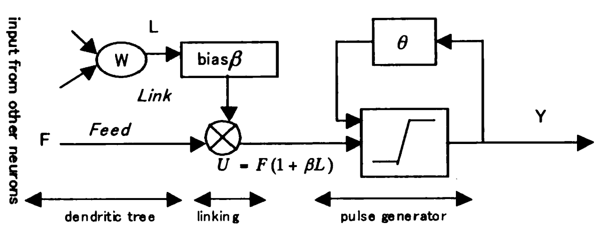



Fig. 1 The pulse-coupled neuron structure model

In the equations (1) and (2), “n” as being the current iteration (discrete time step) is referred, where "n" varies from 1 to N-1 (N - is the total number of iterations; n = 0 is the initial state). The dendrite tree model can be given by the following equations:

$$F_{ij}[n] = e^{-\alpha F}.F_{ij}[n-1] + V_F.\sum_{kl} M_{kl}S_{ijkl} \text{.......................}(1)$$

$$L_{ij}[n] = e^{-\alpha L}.L_{ij}[n-1] + V_L.\sum_{kl} W_{kl}Y_{ijkl}[n-1] \text{..............}(2)$$

Components F and L are called feeding and linking, as two main components of the network. The position of the neuron in the map is determined by (i,j) pair, and time constants for feed and link are $\alpha_F$ and $\alpha_L$. $S_{ijkl}$ is the external stimulus component computed from the pixel intensity (<i+k, j+l>, "<x,y>" denotation the intensity of the pixel with coordinates x and y) in the input image. Usually this value is normalized. $V_F$ and $V_L$ are normalizing constants; M and W denote the constant synaptic weights.

$$f(k,l) = 2 / \sqrt{k^2 + l^2} \text{..................................... ...}(3)$$

Y characterizes the output of the neuron and can only take a binary value of 0 or 1, which is called binary pulse generator.
The linking effect can be represented as follows:

$$U_{ij}[n] = F_{ij}[n].(1 - \beta.L_{ij}[n]) \text{..............................}(4)$$

Uij[n] represents the internal activation or linking modulation of the neuron and ß is the linking weight parameter (bias in Fig. 1). The pulse generator determines the firing events in the model. In fact, the pulse generator is also responsible for the modeling of the refractory period. As the neuron produces a spike, its threshold is raised to prevent it from firing again in the near future (established by the parameter settings). The threshold is then decreased to allow the neuron to fire when its activation is increased.

$$Y_{ij}[n] = \begin{cases} 1, if\ U_{ij}[n] > \Theta_{ij}[n-1] \\ 0, otherwise \end{cases} \text{... ......................... ..}(5)$$

$$\Theta_{ij}[n] = e^{-\alpha\Theta}.\Theta_{ij}[n-1] + V_\Theta.Y_{ij}[n] \text{... .....................}(6)$$

In the equations (4) and (5), $\Theta_{ij}[n]$ correspond to the dynamic threshold of the neuron while $\alpha_\Theta$ and $V_\Theta$ are the time constant and the normalization constant respectively. Throughout the simulation, each iteration renovates the internal action and the output for each neuron in the network, based on the stimulus signal from the image and the prior condition of the network. For each iteration, the total amount of firings (Eq. 5) over the whole PCNN is calculated and accumulated in a global array G (PCNN signal), and then the DFT (Discrete Fourier Transform) is used to calculate the global array G.

$$G[n] = \sum_{ij} Y_{ij}[n], \text{ where n is iteration (n..N-1)} \ldots \quad (7)$$

### 2.1 ROI Identification System

Fig.2 shows the block diagram of the identification system process.

*Step 1: The input image is smoothed by a PCNN to reduce the effects of random noise.*

Image smoothing using PCNN is accomplished by modifying the intensities of noisy pixels based on the neuron firing patterns. In general, the intensity of a noisy pixel is expected to be significantly different from the intensities of the surrounding pixels. Therefore, neurons corresponding to the smoothed image of the tank are applied as input to the segmentation module, which is also a PCNN.

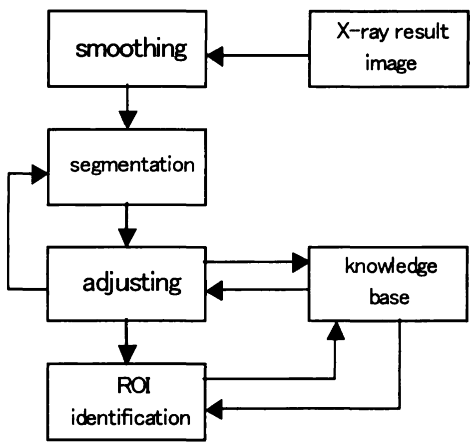



Fig. 2 Block Diagram of Identification System

*Step 2: The image is segmented into several regions using a PCNN.*

The general approach to segment images using PCNN is to adjust the parameters of the network so that the neurons corresponding to the pixels of a given region pulse together and the neurons corresponding to the pixels of adjacent regions do not pulse together.

Assume that the image to be segmented consists of regions and is applied as input to a PCNN. The network neurons pulse based on their feeding and linking inputs. Note that the feeding input to a neuron is equal to the intensity of its corresponding pixel. Due to the capture phenomenon the neurons associated with each group of spatially connected pixels with similar intensities tend to pulse together. Thus, each contiguous set of synchronously pulsing neurons identifies a segment of the image. The value of the linking coefficient $\beta$ has significant effect on the segmentation process. If the value of $\beta$ is low, the pixels that belong to a single region are partitioned by the PCNN into several segments. This is known as over-segmentation. On the other hand, if the value of $\beta$ is high, the PCNN groups pixels that belong to two or more regions to form a single segment. This is known as under segmentation. It may be possible to find the optimal value of $\beta$ based on the intensity probability density function of the image and the geometry of objects present in the image.

*Step 3: Matching test X-ray image with the information in adjusting module and database.*

Next, identification module with its information about PCNN constants, which are used in adjusting module and the information of the tuberculosis level and other identity in database, are matched.

### 2.2 Identification Module

The model proposed here is based on three modules of processing: the pulse-coupled neural network (PCNN) module, the Discrete Fourier Transform (DFT) module and the identifier modules as well as multilayer perceptron (MLP) and Kohonen network (Fig.3). Information flow is mainly feed-forward but there are also lateral interactions between the pulse-coupled neurons.

### 2.3 Discrete Fourier Transform (DFT)

The following equations is the standard analysis that used to calculate the DFT:

$$\mathrm{Re}\,X[k] = \sum_{i=0}^{N-1} G[i]\cos(2\pi ki / N), k = 0..N/2 \;... \qquad (8)$$

$$\mathrm{Im}\,X[k] = -\sum_{i=0}^{N-1} G[i]\sin(2\pi ki / N), k = 0..N/2 \;... \qquad (9)$$

Calculating the DFT means fundamentally correlating the input signal with each basis function. The DFT obtains two shorter signals to be analyzed. Based on the experimental observations shows that the real part all over the testing images is relative stable. Thus the only imaginary part of the DFT is used in advance processing, however, a mixture perhaps greatly achievable.

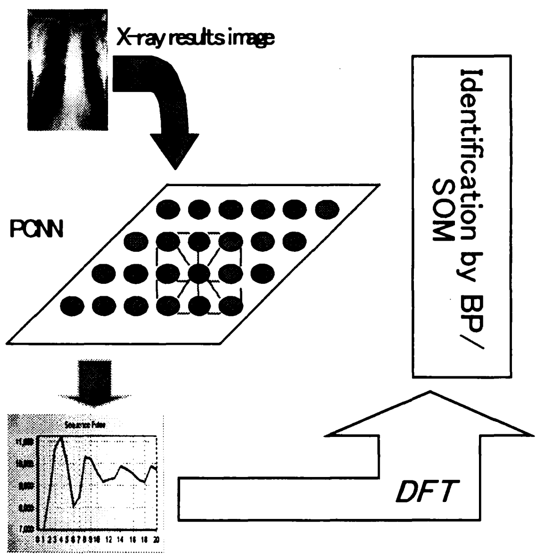
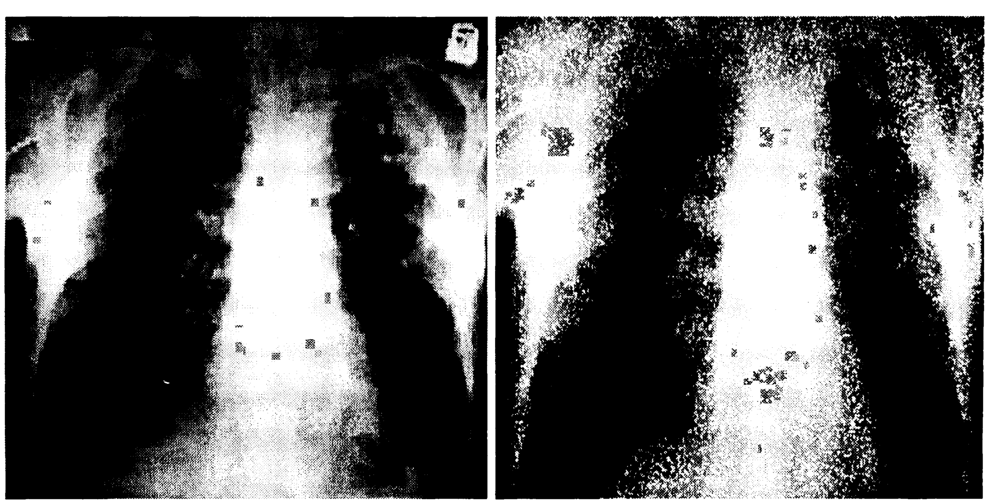



Fig. 3 Identification module architecture

## 2.4 Identifier

There are two methods that used to identify the image patterns, the first is a multilayer perceptron (MLP), and the second is Kohonen method. The MLP structure consists of an input layer, a hidden layer and an output neuron. The input layer contains a number of inputs equal to the samples in the imaginary part of the DFT signal (Im X in eq. (9)). Then, a hidden layer has a broadening of the input layer. The output layer is contained only one neuron (target recognition). An output value of 1 is corresponding to target recognition while a value of 0 earnings no target recognition. A typical backpropagation algorithm is used for the learning process [1,3].



(a) (b)
Fig. 4 X-ray image : (a). original; (b). noising by AWGN (1.5%)

## 3. Experimental Results And Analysis

### 3.1 Capturing X-ray of Lung Image

There are some X-ray images of lung with adjusted *noise (Adaptive White Gaussian Noise)* as an example is Fig.4 b, for comparing with the original one (Fig.4a), and calculating each identification module performance.

### 3.2 Image Smoothing using PCNN

There is restoration and smoothing module for noisy image using PCNN method. The following optimal constants is used for smoothing: *linking coefficient,* $\beta = 0.02$*, radius linking effect coefficient,* $r = 1.5$, adjustment pixel constant, $\Delta = C = 15$, with 25 iterations ($N = 25$). Fig.5 is the result of smoothing Fig.4 b by using PCNN.

Fig. 5 Image Smoothing result using PCNN

Processing time for image restoration with size of image is 300x240 pixels, and PCNN parameters are shown in Table 1:

Table 1 Processing time for image restoration

| No | Image size (width x height) | Iteration | Delta (Δ) | Beta (β) | Time |
|---|---|---|---|---|---|
| 1 | 300x240 | 30 | 15 | 0.07 | 00:00:17:6 |

### 3.3 Image Segmentation using PCNN

Image segmentation by using PCNN is done by giving a sharp contrast between the object and background. The PCNN, by the virtue of the capture phenomenon, is capable for producing good segmentation results even when the input images are noisy and inadequate of contrast. The coefficients are: $\beta = 0.07$, $r = 1.5$, $N = 1$ (Fig. 6) After those two steps (Restoration and Segmentation), the X-ray images will enter the real process, namely, Identification Module. Processing time for segmentation is described in Table 2:

Table 2 Processing time for image segmentation

| No | Image size (width x height) | Iteration | *Increment* Beta (β) | Beta (β) | Time |
|---|---|---|---|---|---|
| 1 | 300x240 | 30 | 0.005 | 0.01 | 00:00:03:1 |

Fig. 6 Image Segmentation result using PCNN

### 3.4 ROI Identification using PCNN

In identification process, an image is processed in three phases:

1.Creating PCNN signal which is the morphology presentation of each X-ray image (Fig.7) .The signal is the sum of firing state (Y = 1) of every iteration. The coefficients are: $\beta = 0.02$, $r = 1.5$, $N = 20$.

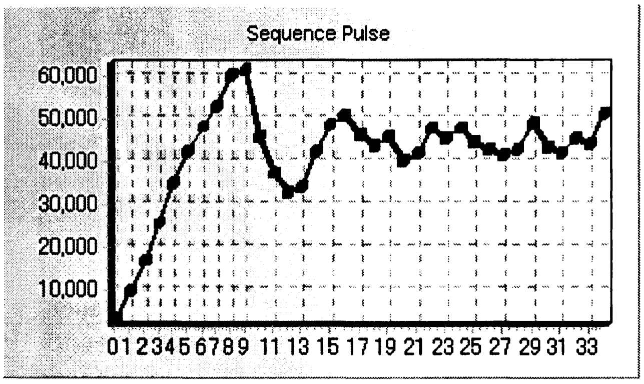



Fig.7 PCNN signal of Chest image on Fig.6

2.Simplify the PCNN signal into Frequency domain and discrete signal using DFT. The imaginary part of the discrete signal is used for determining the characteristic of image (Fig.8).

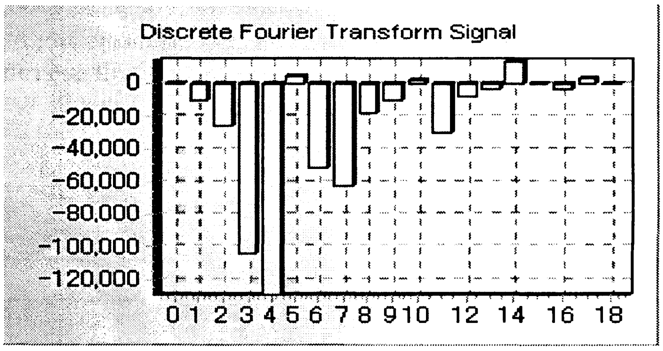
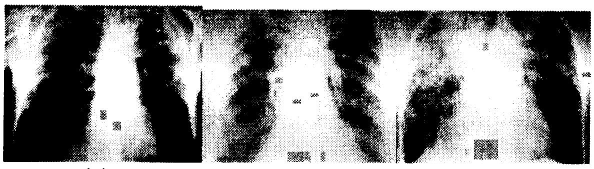



Fig.8 DFT imaginer signal of Fig.7

3.Classified the output of DFT into Backpropagation or Kohonen process. To avoid complicated process, a simple architecture of Kohonen network with 25x25 *winning node* and, *the learning rate, $\alpha$ = 0.73* is used. For instance, from those three X-ray image on Fig.9, then, identify (detect) one of them (ex. Fig .9c), and determine the winning node of each image.



(a) (b) (c)

Fig .9 X-ray image : (a) image1 (vector 0); (b) image2 (vector 1); (c) image 3 (vector 2)

Learning process is done with 10 (N = 10) iterations and the results are:

Learning Result Detail for each Target

Vector 0 :19 22

Vector 1 :19 23

Vector 2 :19 21

End of Learning Result Detail

After the application testing process on image 3 (vector 2), the Kohonen output is obtained as follows (image 3 is detected successfully):

Output for the current images:

Vector 2 :19 21

### 3.5 Image Identification using Backpropagation

The sum of identified images (application testing process) compared to the learned images (learning process) using Backpropagation with their learning time can be seen as follows:

Table 3 Backpropagation Classifier Testing

| No | Learned target | Detected target | *hidden layer nodes* | Iteration | Time |
|---|---|---|---|---|---|
| 1 | 10 | 10 | 12 | 5000 | 00:00:05:3 |
| 2 | 20 | 20 | 25 | 8500 | 00:00:15:7 |
| 3 | 25 | 25 | 30 | 8500 | 00:00:26:4 |
| 4 | 30 | 30 | 35 | 8500 | 00:00:41:3 |
| 5 | 43 | 43 | 45 | 10000 | 00:02:00:8 |

All the learned targets are identified successfully (100 %), with incrementally hidden layer nodes. If the number of node are larger, a longer processing time is acquired, however, larger iteration and targets only affect a little increment in the processing time. Backpropagation is very well at identifying a lot of targets, but will take a long time for learning time and processing time.

### 3.6 Image Identification using Kohonen

The table of identification results for Kohonen Classifier processing is:

Table 4 Kohonen Classifier testing

| No | Learned targets | Detected target | Beta | Dec Beta | Iteration | Time |
|---|---|---|---|---|---|---|
| 1 | 10 | 10 | 0.55 | 0.3 | 10 | 00:00:00:3 |
| 2 | 20 | 19 | 0.7 | 0.9 | 60 | 00:00:00:9 |
| 3 | 30 | 25 | 0.7 | 0.9 | 65 | 00:00:01:5 |
| 4 | 40 | 30 | 0.7 | 0.9 | 70 | 00:00:02:1 |
| 5 | 43 | 33 | 0.7 | 0.9 | 75 | 00:00:02:8 |

*Kohonen* requires many parameters, which have to be modified for incrementally target. If the network has to learn a larger amount of target, less detected targets will be identified by Kohonen. However, Kohonen enables to learn in such a short time for the same amount of target with Backpropagation with a smaller iteration (<100), Therefore, Kohonen only needs less than 2 seconds to learn 40 targets, thus, Kohonen is the faster method.

## 4. Concluding Remarks

### 4.1 Conclusions

1. PCNN has a better reliability in pre-processing noisy image compared to median filter for restoration, Sobel or Canny for segmentation. It happens because PCNN is identifying the *linking field* of the pixels (neurons).
2. PCNN can be implemented in real world application, because it has good pre-processing and learning time, and enables to save a big amount of targets, and the hardware (on a chip IC) is also possible to be made.
3. *Backpropagation* as *Classifier* needs longer learning time, but it enables to handle large amount of targets (100% identified), and very good at identifying noisy image. However, *Classifier* by *Kohonen* have a weakness at detecting large amount of target (93% detected), and not good at handling noisy image, but it has the fastest processing and learning time (< 2 sec), thus, it can be used as an alternative method.

### 4.2 Suggestions

1. The images should be dynamic; consequently, PCNN will become the reliable method in pattern recognition.
2. The system should be developed perfectly in a network system of the medical imaging with server and client (user), the users only access client for identifying medical image, and the administrator is the person who has the responsibility for making sure all the learning and testing process.

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