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ADAPTIVE PCNN CLASSIFIER BASED AUTOMATIC VIRUS PARTICLE SELECTION

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ABSTRACT

Automatic detection of micro particles helps to avoid human intervention in image processing. The existing method of detection of biological virus molecules based on entropy approach cannot detect the damaged particles, low accuracy in particle selection, and is suffer from fixed threshold values. These problems can be overcome by the new adaptive PCNN (Pulse Code Neural Network) Classifier based approach which provides high resolution image reconstruction from low contrasted image. Automatic segmentation and morphological features leads to the initial candidate selection. The image is analyzed in particular ROI, which is defined by overlapping a window with structuring elements over the microscopic image. By keeping the threshold values low, the morphological characters support in detection of candidates and eliminating the false positive particles. These points undergoes credibility test with the help of redial intensity profiles in each points from GLCM feature image and Gabor image. High level PCNN Classifier is used effectively in virus particle selection even they are of damaged particle. It improves the accuracy of selection with the need of low level set features.

KEYWORDS: PCNN (Pulse Coupled Neural Network) Classifier, Human intervention, Automatic segmentation, GLCM (Grey Level Co-occurrence Matrix) and gabor image, threshold values.

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INTRODUCTION

The complete automatic detection of the presence of micro particles from the electron microscopic image is a great achievement of microscopic image processing area. The detection and selection of the virus particles from the transmission electron microscopic image of blood smear is focused here. The viruses are extremely small infectious parasitic agents that aggresses cells of all types. Once it affects any cell it will control that cell and they will replicate by it. They will cause several diseases like common cold, the flu, chickenpox, cold sores etc and serious diseases like Ebola ,AIDS, hepatitis etc. so the detection of those particles are very urgently needed. Most viruses are of icosahedral shape and are about one one-hundredth the size of the average bacterium.

The viruses are too small to be seen directly with an optical microscope and have a diameter only between 20 and 300 nanometers Now the detection of particles is carried out with the naked eyes of experienced human expert medical specialist operators which have a bottleneck for high throughput or determination of structures by reconstruction and the result depends on their skill and expertise. Large number of particles is needed for better resolution. The viruses in the image have varying orientation, shapes and size. The noises in the image are also very high which leads to the need high magnification of the image. The TEM helps to detect most of the virus particles with its advanced characteristics and quality, which is the reason to call it as 'catch all' method without the need of any prior information. Even the electron microscopes are present in most of the hospitals and research centers, the samples are sent to the national diagnostic centers which cause loss in valuable time. Thus developing fully automated approaches for detection of particles are very severely needed.

PREVIOUS WORK

Several large numbers of researches are completed till now to avoid the need for human intervention in detecting the microscopic particles. The fully automatic approaches are the endument in micro particle selection.

Model-based particle picking for cryo-electron microscopy (H. Chi Wong, Jindong (JD) Chen, FabriceMouche, Isabelle Rouiller, 2004), for picking the particle from cryo electron microscopy. The algorithm starts from a crude 3Dmap of the target particle, computed

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from a relatively small number of manually picked images, and then projects the map in many different directions to give synthetic 2D templates. The templates are clustered and averaged and then cross-correlated with the micrographs. The particle picking algorithm is based on a probabilistic model of cryo-EM imaging. Probabilistic scoring then screens the cross-correlation peaks based on likelihood ratios: the probability that a peak was produced by a projection of the 3D map, compared to the probability that it was produced by noise alone. It applies to all "round" particles, there is neither feature computation nor training, and it ranks candidates.

Cross point method (CP) is used in Identification of Spherical Virus Particles in Digitized Images of Entire Electron Micrographs (Ioana M. Boier Martin, Dan C. Marinescu, Robert E. Lynch, 1997). Two algorithms for processing large images, one based on image subsampling, the other on image decomposition, are also proposed. The two algorithms used are stack algorithm and coloring algorithm. A large image is first compressed and the CP method is applied to the compressed image to produce an initial solution. The information gathered at this stage is used to cut the original image into sub-images and then to refine the particle coordinates in each sub image. An interactive environment for experimenting with particle identification methods is also described. Template-matching methods produce reasonable results only when applied to images with a good signal-to-noise ratio i.e., formed with medium to high electron dose, and after background variations are minimized or removed. This can works on large or even the compressed images.

Automatic particle picking using diffusion filtering and random forest classification (Paul Joubert, Stephan Nickel, Florian Beck, Michael Habeck, 2009).An automatic particle picking algorithm for processing electron micrographs of a large molecular complex, the proteasome, is described. The algorithm makes use of a coherence enhancing diffusion filter to denoise the data, and a random forest classifier for removing false positives. It uses a training set of manually picked particles. The algorithm consists of the following steps: Segmentation, Normalization, and Denoising, Picking, Alignment, and Classification.

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All these researches have some drawbacks while detecting the particles. Some of the disadvantages of the existing works are lower resolution of the images which leads to false detection of particle, high complexity, less specificity, fails in detection of damaged virus particles etc. This study results that further tools and methods are needed for the automatic and accurate detection of micro particles.

METHOD

Adaptive PCNN classification

For the convenient detection of the virus particles new adaptive Pulse Coupled Neural Network (PCNN) Classifier is used. The new method can overcome the most of problems faced.

PCNN are neural network model developed by modeling a cat's visual cortex and is meant for better performance in biometric image processing. PCNNs have been utilized for a variety of image processing applications such as image segmentation, feature generation and extraction, face extraction, motion detection, region growing, noise reduction, and so on.

The network consists of the input layer, hidden layer and output layer. Number of hidden layer is optional. As the number of hidden layer increases the complexity and contrast of the output also increases. Each neuron in the network represents one pixel in an image, which receives features of each pixel as the external stimulus. Each neuron is connected with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output.

It continues iteratively and PCNN neurons produce a series of pulse outputs which consists of the information of the input image. These data can be utilized for various image processing applications. PCNNs have several significant advantages, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns, etc. This algorithm features an automatic stop mechanism to terminate PCNN's iteration, an output coding algorithm to utilize all output images' information, a pulse-pattern-based method to detect noised

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pixels, and an adaptive synaptic modification algorithm to lower noised pixel's effect on the segmentation process.

MODELS

The system will detect the virus particle with the working of PCNN classification method. Micro particle detection is a very important task in structural biology and microscopic image processing. Fig 1 shows the block diagram of detecting the virus particle by PCNN method.

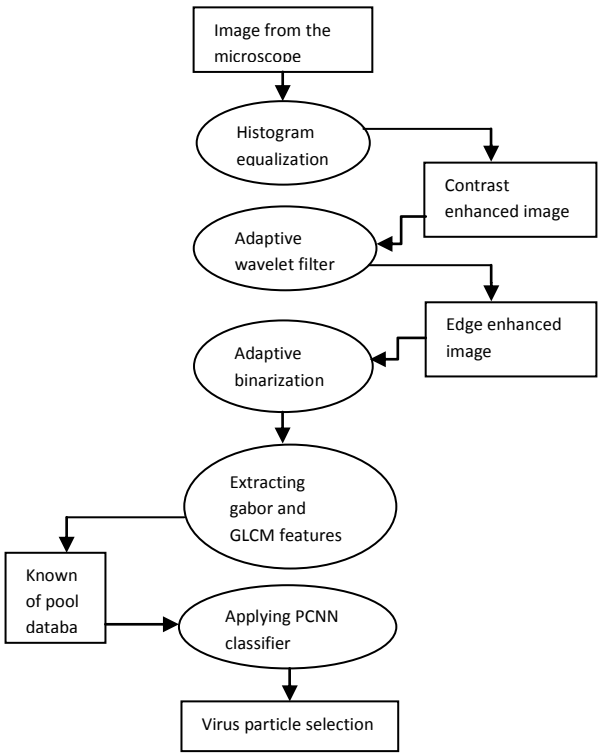

Fig 1: Block diagram of detecting the virus particle.

System Architecture

The microscopic image of the blood smear is taken and which is given as the input to the system. Fif 2 shows the architectural diagramof detecting the virus partivle by PCNN method. The image is then converted to the grayscale image. Preprocessing is applied to the image to filter out and to smooth the fluctuations in it. The image undergoes two preprocessing steps. Preprocessing makes the image clearer to make the detection easily. In preprocessing 1, the background is compensated with the morphological operations with a disk structuring elements of specified pixel size. Then the wavelet spike filter is performed to filter the local spike. Now one percentage of data is saturated. In preprocessing 2, the contrast is enhanced with the adaptive histogram equalization. The remaining noise particles are removed with the wiener filtering method. Again the wavelet filtering is used to enhance the edges of the candidate points. These constitute the second preprocessing. To the same figure the entropy is also calculated. Based on this value the particles with low entropy are calculated as the candidate points. Now the features of the candidate points are tested. The centroid of the candidate points is determined. If the selected

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pixel is at the center of the virus particle, that region will generate a minimum amount of entropy compared to the neighborhood particles. Again the image is filtered to remove the unwanted particles. Finally the image is segmented and candidate points are selected by classifying them with the new adaptive PCNN method. Thus the presence of the virus particle can be confirmed.

IMPLEMENTATION

The system is implemented as four steps.

A. Pre-processing

The pre-processing aimed to smooth the radiometric fluctuations inside the particles and to enhance the borders. The microscopic image can be given as the input image. If the input is a RGB image then it is automatically converted to the gray scale image. Pre-processing can be done with several techniques and methods. The output of the pre-processing is the image with less number of noise particles and more number of candidate particles. Fig 3 shows the contrast enhanced and edge enhanced image. The particles in the image become more enhanced and the contrast of the image is increased, which become easy to perform further steps and easy to determine the original virus particles.

The background is compensated for irregular brightness with a morphological opening with a disk structuring elements, followed by subtraction of the opened image from the original and gray scale adjustment — 1% of the data was saturated at low and high intensities. Pre-processing with a wavelet filter, consisting in decomposition (using a Daubechies wavelet of support of order 11) followed by reconstruction with the details of first level suppressed, provided a smooth filter of local spikes.

Then by contrast-limited adaptive histogram equalization is performed. Here, to an exponential function with parameteralphasetto0.95in8 × 8 tiles, the contrast of the image is enhanced. A pixel wise adaptive Wiener filtering using neighborhoods of several sizes is then performed. The most of the noise particles are removed based on the determined size. Now the image becomes somewhat clearer. To this image, wavelet filter is again applied to enhance the edge of each particle.

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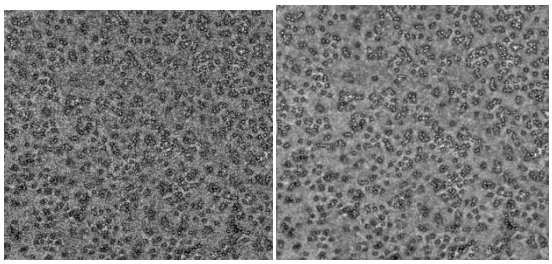

Fig 3: Contrast enhanced and Edge enhanced image.

B. Entropy adaptive threshold

The algorithm for the entropy calculation has three main steps- detection of the candidates, evaluation of the credibility of the location of each point and final validation of the accepted candidates if needed.

After pre-processing, a moving data window was displaced over the image. Entropy values are computed to each window. The ratio can be taken by using these two values, resulted as local entropy proportion (lep). This value corresponds to the central pixel. To find the ratio, the numerator and the denominator are computed in different areas based on three values R, $r_{int}$and $r_{ext.}$ The $r_{int}$and r_{ext} values define an area of interest that encircles the interested particle. When the current pixel is at the center of a virus particle, that pixels will generate a minimum amount of entropy when compared to the neighborhood pixels with same amount of entropy. The area with deepest minima in the entropy proportion image were located using an h-min transform, which select the region whose depth is less than *x*% which is the customized threshold value. Then the morphology operation is performed to isolate that region. The coordinates of the centroid of each of the area are detected and expressed, which defines the coordinates of a candidate point. 7% of the minima are retained and filtered according to morphological criteria. Only small areas and high eccentricities ensure the compact spike typical of the coincidence of the set up with a low entropy area.

C. Feature extraction

Four intensity profiles vertical, horizontal and both diagonals were extracted at each candidate point from the texture image. Several features were computed from these profiles. The features extracted were evaluated against a set of acceptance conditions defined with a set of test images acquired in the same conditions. These include the distributions admissible for the height of the profiles, number of standard widths demanded, and number of intersections admitted, impositions on symmetry and absence of incomplete profiles that must be fulfilled by a candidate point to become an

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accepted point. The remaining points are refused.

D. Candidate point selection

The candidate points are selected with the efficient working of the adaptive PCNN classification method. Fig 4 giving the working model of PCNN classification method. The PCNN algorithm is executed by continual iterations of the following equations:

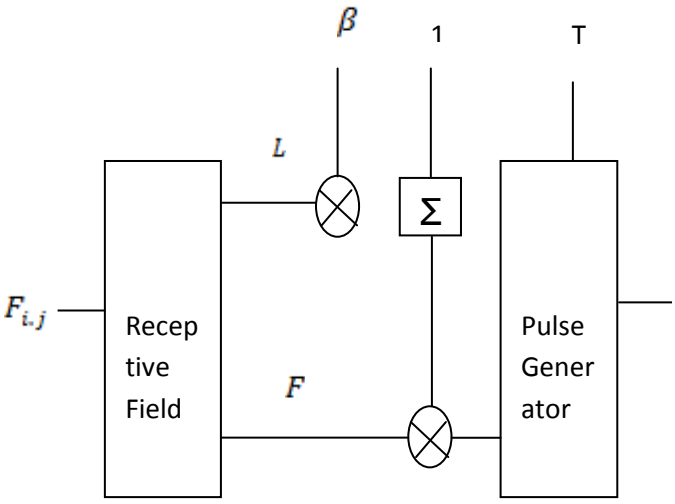

Fig 4 : Model of working of PCNN classification method.

$$F_{ij}[t] = e^{-aF}F_{ij}[t-1] + S_{ij} + V_F\sum_{kl} W_{ijkl}Y_{kl}[t-1]$$

$$L_{ij}[t] = e^{-aL}L_{ij}[t-1] + V_L\sum_{kl} W_{ijkl}Y_{kl}[t-1]$$

$$U_{ij}[t] = F_{ij}[t]\{1+\beta L_{ij}[t]\}$$

$Y_{ij}[t] = 1, if\ U_{ij}[t] >$ $T_{ij}[t-1]; 0, otherwise$; 0 otherwise

$$T_{ij}[t] = e^{-aT}T_{ij}[t-1] + V_T Y_{ij}[t]$$

Where, F, L, U, Y, T represents the feeding input, the linking input, the internal, activation, the output, the dynamic threshold respectively. S is external stimulus, ij is the neuron's position in the network and kl is the co-ordinates (k+1, l+1).

EXPERIMENTAL RESULT

The adaptive Pulse Coupled Neural Network (PCNN) classification detects the virus particles from the microscopic image. New method is efficient to detect the damaged virus particles also. The result can be expected as the comparison with the previous method which is shown in the fig 5.

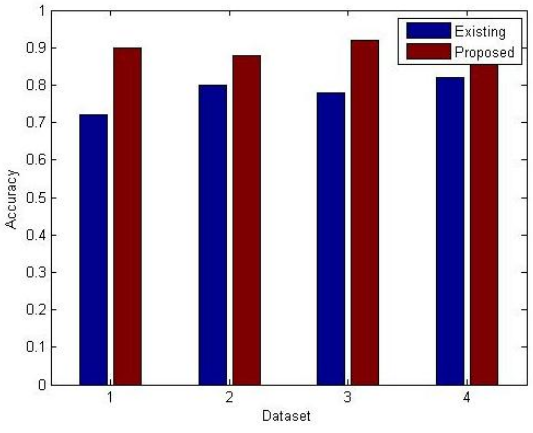

Fig 5: Performance analysis.

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CONCLUSION

The detection of micro virus particle automatically is a tedious task. The researches are going on conducted in this field. The PCNN classifier method helps in detecting the particles efficiently and promoting the accurate selection.

The efficiency of particle detection can be improved further for detecting the newly appearing virus particle as the future work.

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