

Near-Duplicate Image Identification using Pulse Coupled Neural Networks

K. K. Thyagarajan¹

Electronics and Communication Engineering
RMD Engineering College
Chennai, India

V. R. Hasini²

Electronics and Communication Engineering
RMD Engineering College
Chennai, India

A. Jenifer Sweetlin³

Electronics and Communication Engineering
RMD Engineering College
Chennai, India

H. Joshna⁴

Electronics and Communication Engineering
RMD Engineering College
Chennai, India

Abstract: We propose a pulse Coupled Neural Networks for identifying Near-Duplicate images. Temporal series of pulsed output are generated by using pulse coupled neural networks which carries the information about the input image which in turn used to detect NEAR-DUPLICATE images. Near-duplicate images are generated by taking photos of the same scene under different conditions in illuminations, resolutions and so on. Besides they can be formed by modifying the unique images using some transformations(i.e)image rotation ,image mapping, scaling etc. Identifying the near duplicate images plays an important role in many applications such as copyright protection, plagiarism in images, forged images.

Keywords: Near-Duplicate images, Pulse Coupled neural networks, Correlation Coefficient.

I. INTRODUCTION

Near-Duplicate image identification is the task of finding different versions in the same image that has undergone various editing steps such as colour mapping , scaling, format changing ,etc .Near-Duplicates usually occur in web images . The goal of this project is to design a block using PCNN concept, which increase search capacity, accurate answer whether two images are Near- Duplicates and one can easily spot irrelevant images in the search result.

People find less time in analyzing and interpreting solutions for the problems. So people use machines to perform the functions of a human brain.10 billion neurons are present in human brain that are the participants in the parallel information processing system. Pulse coupled neural networks are developed to bring computers a bit closer to the brain's capabilities.

One of the early papers [3] described a dynamic linking architecture based on an excitatory-inhibitory pair of coupled oscillators. Research into more biologically grounded pulsed network dynamics was spurred by the experimental observations of synchronous pulse bursts in the cat visual cortex [21], [2]. The 1990 Eckhorn linking field network [20] was introduced as a phenomenological model of a system exhibiting synchronous pulse bursts. It used a pulse generator called a neuromine, a modulatory coupling term, and synaptic connections modelled as leaky capacitors. Its central new concept was the introduction of a secondary receptive field, the linking field, whose integrated input modulated the primary feeding receptive field input by means of an internal cellular circuit. It provided a simple, effective simulation tool for studying synchronous pulse dynamics in networks, and was soon recognized as having significant applications in image processing [6][7][11]. The PCNN proved its efficiency as a powerful tool for lot of image processing functions such as feature extraction,image segmentation and object recognition[24][8][18][29][27].The significant advantage of PCNN model is that it can operate without any of training

needed. Since introduced by Eckhorn in 1990[20], the model has proven its vital role in digital image processing, such as image segmentation[9], image thinning[14], motion detection[12], pattern recognition[22], face detection[10], etc.

Biological systems have always been an inspiration for developing algorithms. The base of some network models is the mammal's visual cortex. Visual cortex of Cat's and guinea pig's helped in developing some digital models. The input information is received by the eye but the retina is not sensitive to all the information. The sensitivity is based on colour, motion and intensity. The retina after receiving the information alters the behaviour of surrounding receptors with respect to the contents and then forwards to the visual cortex and then the received information is analyzed by the brain. The functioning of the visual cortex has to be studied in order to develop algorithms. This is more complicated than programming of computers. In the late 1980s, Eckhorn et al, discovered that the midbrain in an oscillating way created binary images that could extract different features from the visual impression when they had studied the cat visual cortex. Based on the binary images the actual image is created in cat brain. This discovery led to the development of a neural network, called Eckhorn's model, to simulate this behaviour. Later in 1990s Arndt, Dicke, Eckhorn, and Reitboeck (1990) developed a model on cat's visual cortex. In their model, each neuron received input from its own stimulus and also from the neighbouring neurons. The outputs from other neurons were also an input for the parent neuron. This model provided a simple, effective way for studying synchronous pulse dynamics in networks. These discoveries have paved the way for the generation of pulse coupled neural networks. Later, Johnson et al. carried on number of modifications and variations to tailor its performance as image processing algorithms. This modified neural model is called Pulse Coupled Neural Networks(PCNN). In 1992, Rybak, Sandler, and Shevtsova (1992) introduced a model based on guinea pigs' visual cortex. This model resembles Eckhorn except in equations. An unconventional model was suggested by Combe, Ducom, and Parodi (1996) in which delays were included in synaptic connections.

This paper presents a PCNN structure for near- duplicate image identification. Firstly, we read two RGB images, convert it into gray scale images and the images are normalized. By using PCNN, temporal series of pulsed output is generated for two images. Then the correlation between the outputs generated from two images is evaluated. Since the images are normalized, the pixel intensity values range between 0-1. Finally, if the output displayed is 1, the images match exactly or else the image is nearly duplicate. Here is the structure of the paper. Section 2 gives a brief description about literature survey. The working methodology of PCNN is described in section 3, followed by the algorithm and the experimental result.

II. LITERATURE SURVEY

Amruta Landge and Pranoti Mane [1] proposed Near-Duplicate image matching using PCSLBP and SIFT based variable length signatures which needs the matching of somewhat altered images to the original image. Patch based image matching method shows good robustness to image scale in orientation invariance. Li Liu, Yue Lu [15] proposed the representation of an image by a signature, the length of which varies with respect to the number of patches in the image. Beyond each individual patch, the spatial relationships among the patches are captured. Near-duplicate document image retrieval and near- duplicate natural image detection is evaluated by image signatures. G.Kalaiarasi and K.K.Thyagarajan [4] proposed the classification of near-duplicate images based on fuzzy support vector machine. First gray level co-occurrence matrix is used to extract texture features. Next extracted features are given as input to SVM. Finally, fuzzy is incorporated with SVM classifier to classify near duplicate images. G. Kalaiarasi and K.K.Thyagarajan [5] proposed clustering of near duplicate images in the search using affine transform and hybrid hierarchical k-means algorithm to detect new duplicates and cluster those images. This is done by using three steps—image preprocessing, feature extraction and clustering. Kavitha Srinivasan, K.K.Thyagarajan[13] proposed dual channel pulse coupled neural networks algorithm for fusion of multi modality brain images and the fused image is further analyzed using subjective (human perception) and objective (statistical) measures for quality analysis. Mariusz Paradowski, Mariusz Durak and Bartosz Broda [17] proposed Bag of words- quality issues of Near-Duplicate image retrieval which addresses the problem of large scale near duplicate image retrieval. Issues related to visual words dictionary generation are discussed. A new spatial verification routine is proposed. It incorporates neighbourhood consistency, term weighting and it is

integrated into the bhattacharyya coefficient. The proposed approach reaches almost 10 percent retrieval quality comparing to other recently reported state-of-the-art methods. Trong –Thuc Hoang , Ngoc-Hung Nguyen , Xuan-Thuan Nguyen and Trong-Tu Bui [28] proposed two hardware architecture based on PCNN for image feature vector extraction . Based on these architecture the demonstration recognition system including a camera ,a feature vector generator ,a search engine and a DVI controller has been built and tested successfully on FPGA chips. M. Monica Subashini , Sarat Kumar Sahoo[16] proposed Pulse coupled neural networks and its applications that surveys the extensive usage of pulse coupled neural networks. The visual cortex system of mammals was the backbone for the development of pulse coupled neural network. PCNN (Pulse Coupled Neural Networks) is unique from other techniques due to its synchronous pulsed output, adjustable threshold and controllable parameters. Ondrej Chum, James Philbin and Andrew Zisserman[19] proposed Near -Duplicate image detection using Min-Hash and tf-idf weighting proposed image similarity measures for fast indexing via locality sensitive hashing. The similarity measures are applied and evaluated in the context of NDID . The proposed method uses a visual vocabulary of vector quantized local feature descriptors (SIFT) and for retrieval exploits enhanced Min -Hash techniques . R. Eckhorn, H.J. Reitboeck, M. Arndt, P.W Dicke[21] proposed A neural network for feature linking via synchronous activity: results from cat visual cortex and simulation they discovered stimulus-specific interactions between cell assemblies in cat primary visual cortex that could constitute a global linking principle for feature associations in sensory and motor systems: stimulus-induced oscillatory activities (35-80 Hz) in remote cell assemblies of the same and of different visual cortex areas mutually synchronize, if common stimulus features drive the assemblies simultaneously.

III. METHODOLOGY

Pulse coupled neural networks are neural models proposed by modelling a cat's visual cortex and developed for high performance biometric image processing . The PCNN is a two-dimensional neural network of incorporate- and- let off neurons, with a 1:1 correspondence between the image pixels and the network neurons. Basic pulse coupled neural network is shown in fig 2.

The pulse coupled neural networks has three compartments:

- (1) Receptive field
- (2) Linking part or modulation
- (3) pulse generator

Receptive field is primary part to receive input signals from the neighbouring neurons and from external sources and the field have two internal channels known as Feeding compartment F and Linking compartment L . The linking inputs have faster characteristics response time constants when compared to feeding connections.

A PCNN is a single layer laterally connected network. Each neuron in the network corresponds to one pixel in an input image corresponding pixel's colour information (e.g. intensity) as an external stimulus. Each neuron pairs up with its neighbouring neurons, receiving local stimuli from them . The external and local stimuli are put together in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold , resulting in pulse output. Through iterative computation , PCNN neurons produce temporal series of pulsed outputs. The temporal series of pulsed outputs contain information of input images and can be used for the identification near-duplicate images. The PCNN concept works on these following mathematical equations.

The compartments' output is determined by the following equations:

$$F_{ij}[n] = e^{\alpha_F \delta_n} F_{ij}[n-1] + S_{ij} + V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1]$$

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

S_{ij} is the input stimulus of image pixels in(i,j) position, $F_{ij}[n]$ is a primary feeding slot(i,j) neuron, $L_{ij}[n]$ is the output of the linking slot Y_{kl} is the output of neurons from previous iteration. M_{ijkl} and W_{ijkl} is the constant gaussian weight functions with the distance. V_F and V_L is the inherent voltage potentials. α_F is the attenuation time constant of $F_{ij}[n]$ and α_L is the attenuation time constant of $L_{ij}[n]$.

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

$$Y_{ij}[n]=\begin{cases} 1 & U_{ij}[n] > T_{ij}[n] \\ 0 & \text{otherwise} \end{cases}$$

$$T_{ij}[n]=e^{-\alpha_T T_{ij}[n-1]}+V_T Y_{ij}[n]$$

β is the connecting coefficient. $U_{ij}[n]$ is the internal activity of neuron, $T_{ij}[n]$ or θ_{ij} is the dynamic threshold, α_T is the attenuation time constant of $T_{ij}[n]$, $Y_{ij}[n]$ represents the pulse output of neuron and it gets either the binary value 0 or 1. For the feeding channel, α_F determines the rate of decay of the feeding channel. Larger α_F causes faster decay of the feeding channel. V_F can enlarge or reduce the influence from surrounding neurons. Matrix W refers to the mode of interconnection among neurons in the feeding receptive field. Usually, the size of W denotes the size of the feeding receptive field. The value of matrix element W_{ijkl} determines the synaptic weight strength. In most cases, this channel simplifies via $\alpha_F=0$ and $V_F=0$. Unlike from the feeding channel, the linking channel generally keep itself as it is. The link channel also has three parameters (α_L, V_L and M) that have the same function to the parameters (α_F, V_F and M) respectively. Usually, the inter-connection employs the Gaussian weight functions with the distance.

The connecting coefficient β is an important parameter, because it can vary the weighting of the linking channel in the internal activity. Hence, its value is usually depended on different demands. For example, if much influence from the linking channel is expected, β should be given larger value. All neurons often have the same value of β . It is not fixed, Each neuron can have its own value of β . For the pulse generator, α_T indicates the rate of decay of the threshold in the iterative process. Because it directly decides the firing time of neuron, is a significant parameter. Smaller α_T can make the PCNN work in a meticulous way but it will take much time to finish the processing. On the contrary, large α_T can decrease more running time of PCNN. V_T decides the threshold value of fired neuron. If expecting that neuron just fires one time you can give α_T a huge value.

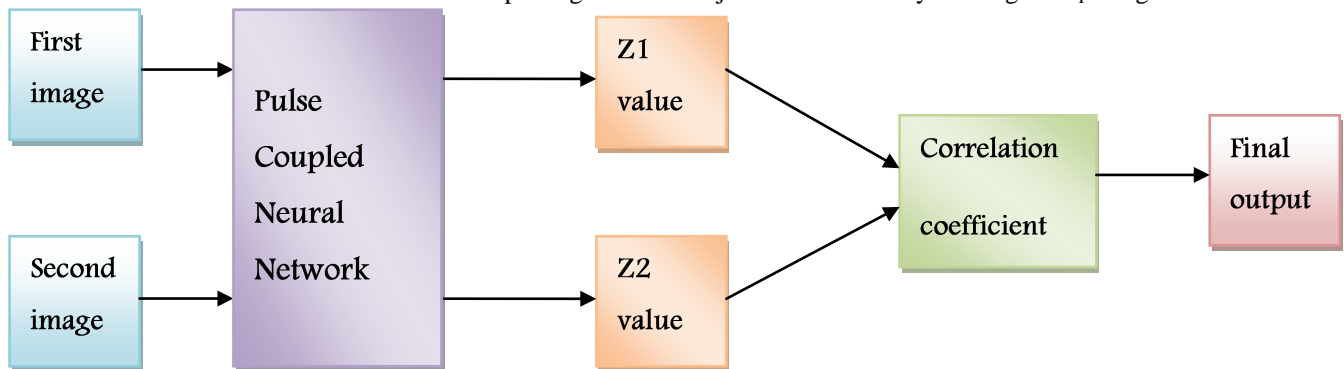


Fig.1.Near-Duplicate image identification using PCNN block diagram

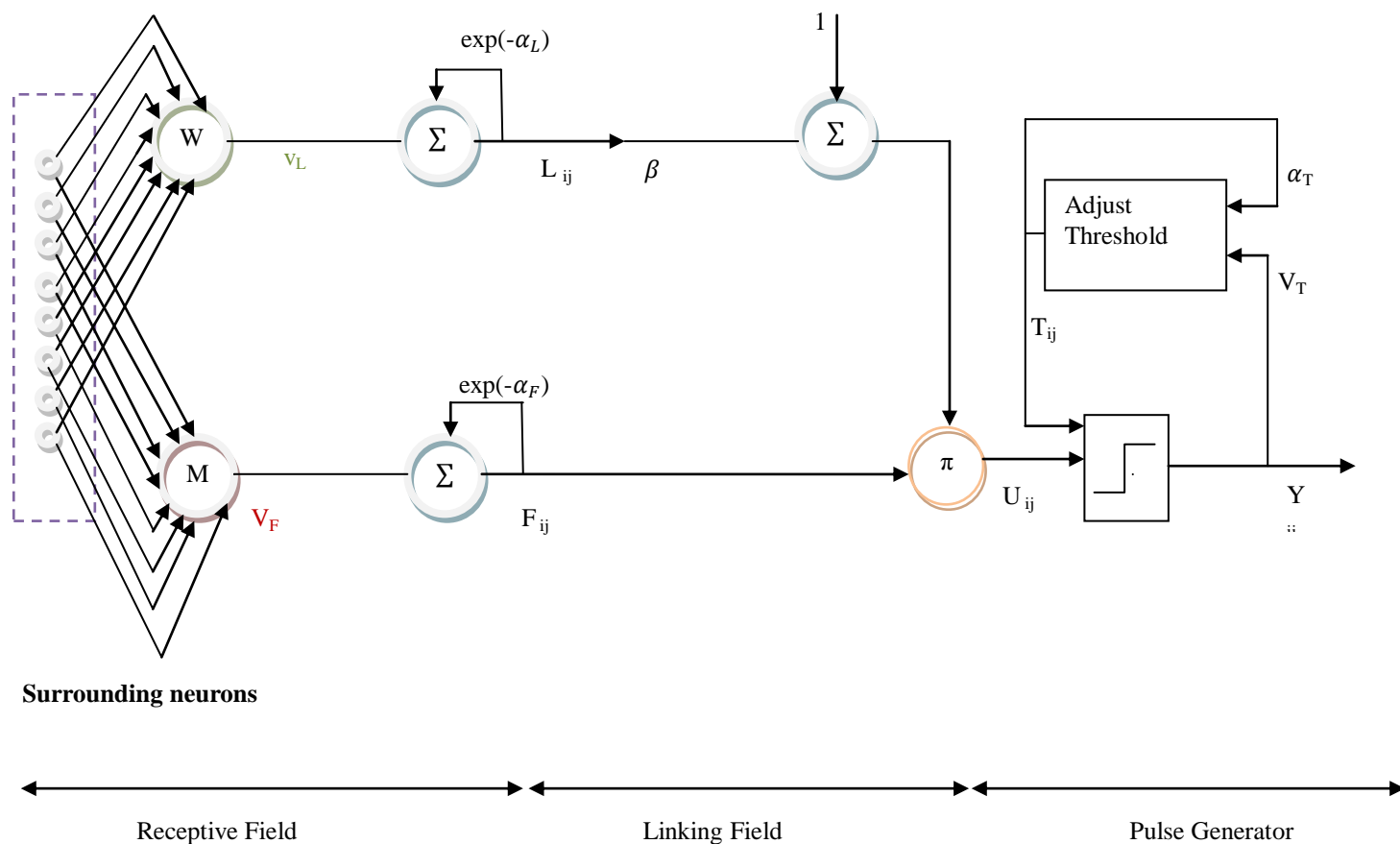


Fig. 2. Pulse coupled neural networks model

The above PCNN concept is implemented using MATLAB software which is developed by the MathWorks. Inc is a high-performance language for technical computing. It integrates computation, visualization and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notations. PCNN concept can also be implemented in hardware (i.e) FPGA.

CORRELATION COEFFICIENT

Correlation is a mutual link between two or more images. Correlation is an arithmetical measure that indicates the degree to which two or more variables fluctuate together. A affirmative correlation indicates the degree to which those variables increase or decrease in the same manner. A negative correlation indicates the degree to which one variable increases as the other decreases. A correlation coefficient is an arithmetical measure of the extent to which changes to the value in one variable predict change to the value of another. Correlation can alter from +1 to -1. Values close to +1 indicate high degree of positive correlation and values close to -1 indicates high degree of negative correlation. Values close to 0 indicate poor correlation of either kind.

ALGORITHM

- Step1: Read the input image and convert it to gray scale image.
- Step 2: Set decay term for feeding(α_F), linking(α_L) and threshold (α_T).
- Step3: Set the magnitude scaling term for feeding(V_F), linking(V_L) and threshold(V_T).
- Step 4 :Set the linking strength(β).
- Step 5: Specify the number of iterations.
- Step 6: Set the initial values for W, M, F, L, Y, U, T .
- Step 7: Normalizing the values to lie within $[0,1]$.

Step 8: Update the feeding and linking input.

$$F_{ij}[n]=e^{\alpha_F \delta_n} F_{ij}[n-1]+S_{ij}+V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1]$$

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

Step 9: Compute the internal activation.

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

Step 10: Update the threshold input.

$$T_{ij}[n]=e^{-\alpha_T} T_{ij}[n-1]+V_T Y_{ij}[n]$$

Step 11: Update the output Y based on internal activity(U) and threshold(T).

$$Y_{ij}[n]=\begin{cases} 1 & U_{ij}[n] > T_{ij}[n] \\ 0 & \text{otherwise} \end{cases}$$

Step 12: Compute the final output Z based on the previous iterated value of Z and the current value of Y.

Step 13: Correlation between two outputs from two images are evaluated using correlation coefficient function.

Step 14: If the output displayed is 1, the images match exactly or else the image is nearly duplicate.

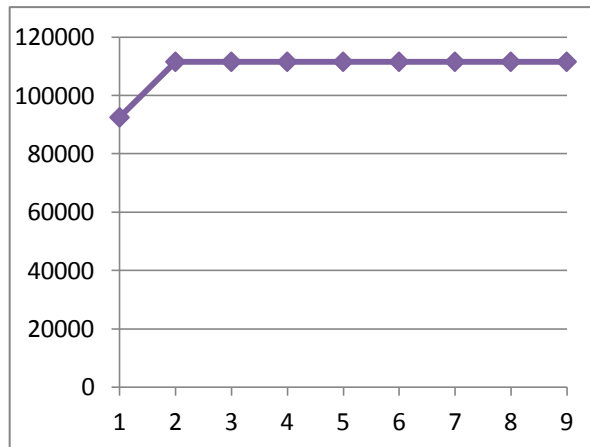
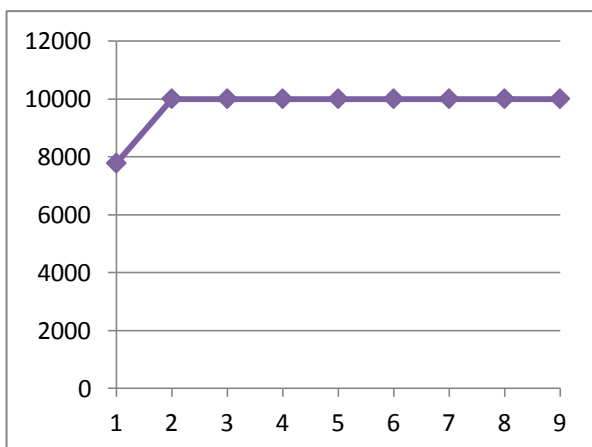
IV. EXPERIMENTAL RESULTS AND ANALYSIS

To estimate the efficiency of the proposed algorithm, experiments are conducted with the standard test image lena100.jpg and a sample image lena1_-22.5.jpg.



Fig.2. Input image (a) lena100.jpg (b) lena1_-22.5.jpg (c) lena 400x200.jpg (d) lena 400x200.jpg

The number of iterations is assumed to be 10. A line graph is obtained with the Z values(entropy) and the number of iterations, for both lena100.jpg and lena1_-22.5.jpg and then for lena 400x200.jpg and Hydrangeas.jpg



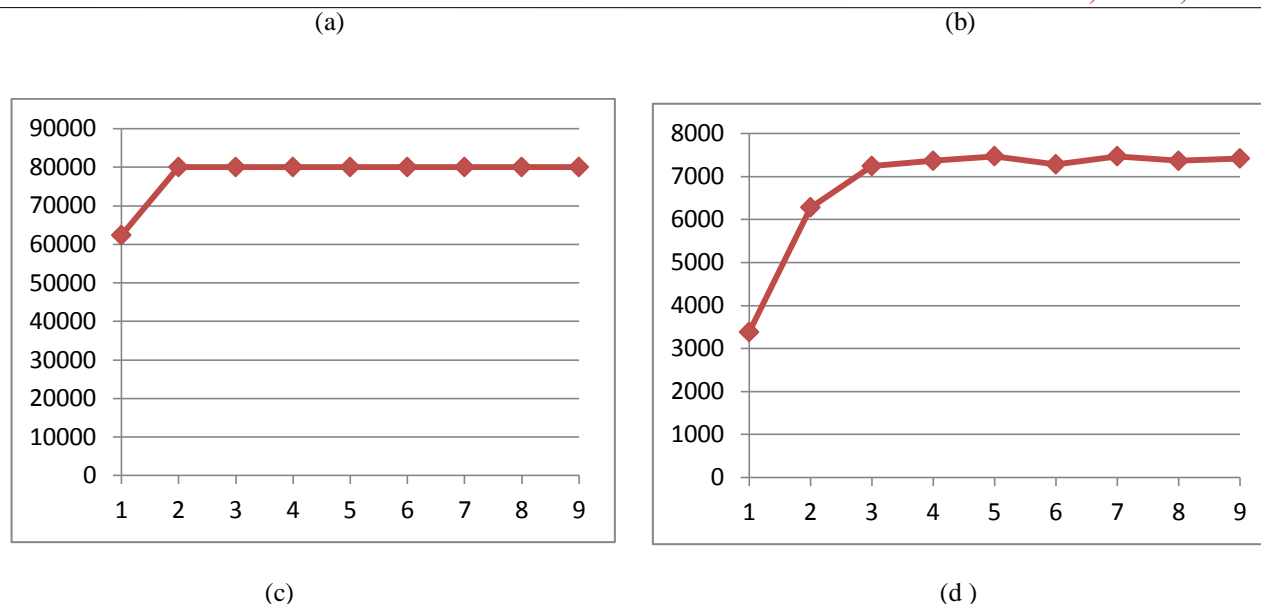


Fig.3.entropies w.r.t no.of.iterations for (a)lena100.jpg (b)lena1_-22.5.jpg (c)lena400x200.jpg (d)Hydrangeas.jpg

Standard image of lena100.jpg and Sample image of lena1_-22.5.jpg is considered. From figure 3(a) and (b) it can be concluded that the sample image is nearly duplicate to the standard image.

If I_1 and I_2 are two images the cross correlation between these two images are defined by

$$\frac{\sum_{ij}(I_{1,ij} - \bar{I}_1)(I_{2,ij} - \bar{I}_2)}{\sqrt{\sum_{ij}(I_{1,ij} - \bar{I}_1)^2} \times \sqrt{\sum_{ij}(I_{2,ij} - \bar{I}_2)^2}}$$

Where i,j are the coordinates of the pixels. The correlation between two image entropies is evaluated using a line chart, by applying the above formula, then the value is found to be **0.9987** (i.e) high degree towards positive correlation. Finally, the standard image lena100.jpg and the sample image lena1_-22.5.jpg is found to be nearly duplicate.

Standard image of lena400x200.jpg and Sample image of Hydrangeas.jpg is considered. From figure 3(c) and (d) it can be concluded that these two images are different. The correlation between two image entropies is evaluated using a line chart, by applying the above formula, then the value is found to be **0.9417** which indicates a diverse image.

When the standard image is identical to the sample image then the correlation between the two image entropies is **1**, which indicates there is no duplication. Finally by using Pulse Couple Neural Networks Near-Duplicate images are identified, which can be used in various applications such as

- (1) To identify forged images.
- (2) Can be used in copyright protection.
- (3) Helps in searching an image out of several millions of images stored in the internet.
- (4) Image plagiarism.
- (5) Can be used in security systems.

V. CONCLUSION

In this paper, we discussed how to identify near-duplicate images using PCNN. Duplicate images are easy to identify, whereas near duplicate images are difficult to identify as they differ in small portions due to cropping, scaling, rotations, illuminations, transformations. We found that the proposed method appears to provide the best performance at the cost of higher computational and storage expenses. The proposed system show superior performance in terms of accuracy and speed.

References

1. Amruta Landge and Pranoti Mane "Near-Duplicate image matching using PCSLBP and SIFT based variable length signatures", Special Issue on International Journal Of Electrical Electronics And Computer System, vol.4,2347-2820, Feb 2016.
2. C. M. Gray and W. Singer, "Stimulus-specific neuronal oscillations in the orientation columns of cat visual cortex," Proc. Nat. Academy Sci., vol. 86, pp. 1689–1702, 1989.
3. C. Von der Malsburg and W. Schneider, "A neural cocktail party processor," Biol. cybern., vol. 54, pp. 29–40, 1984.
4. G. Kalaiarasi and K.K. Thyagarajan, "Classification of near- duplicate images by texture feature extraction SVM", Advances in Engineering and Technology , pp 187-194.
5. G. Kalaiarasi and K.K. Thyagarajan, " Clustering of near Duplicate Images in the Search Using Affine Transform and Hybrid Hierarchical K-means (HHK) Algorithm", WIT Transactions on Information and Communication Technologies 60:239 – 246 · December 2014.
6. H. J. Reitboeck, R. Eckhorn, M. Arndt, and P. Dicke, "A model of feature linking via correlated neural activity," in Synergetics of Cognition, H. Haken, Ed. New York: Springer-Verlag, 1989, pp. 112-125.
7. H. S. Ranganath, G. Kuntimad, and J. L. Johnson, "Pulse coupled neural networks for image processing," in Proc. 1995 IEEE Southeast Con, Raleigh, NC, 1995, pp. 37–43.
8. H. Kurokawa, S. Kaneko, M. Yonekawa, " A color image segmentation using inhibitory connected pulse coupled neural networks" , Lecture notes in computer science, advances in neuro-information process; vol 5507, 2009 ,pp 776-783.
9. Henrik Berg, Roland Olsson, Thomas Lindblad, Jos Chilo, "Automatic design of pulse coupled neuron for image segmentation," Neurocomputing, Vol. 71, Issues 10-12, pp. 1980-1993, June 2008.
10. Hitoshi Yamada, Yuuki Ogawa, Kosei Ishimura Mitsuo Wada, "Face Detection using Pulse-Couple Neural Network," In Proc. SICE Annual Conf Vol. 3, pp. 2784-2788, Aug. 2003.
11. J. L. Johnson, H. Ranganath, G. Kuntimad, and H. J. Caulfield, "Pulse coupled neural networks," in Neural Networks and Pattern Recognition, O. Omidvar and J. Dayhoff, Eds. San Diego, CA: Academic, 1998 pp. 1–56.
12. Jun Chen, Kosei Ishimura, Mitsuo Wada, "Moving Object Extraction Using Multi-Tiered Pulse-Couple Neural Network," In Proc. SICE Annual Conf Vol. 3, pp. 2843-2848, Aug. 2004.
13. Kavitha Srinivasan, Dr. K.K. Thyagarajan , "Dual channel pulse coupled neural networks algorithm for fusion of multi modality brain images with quality analysis", Applied medical informatics vol 35, No 3 (2014).
14. Lifeng Shang, Zhang Yi, "A class of binary image thinning using two PCNNs," Neurocomputing Vol. 70, Issues 4-6, pp. 1096-1101, Jan. 2007.
15. Liu L , Lu Y, Suen CY, "Variable- length signature for near- duplicate image matching" , IEEE Transaction image processing , vol. 24 , issue 4, april 2015.
16. M. Monica Subashini , Sarat Kumar Sahoo, " Pulse coupled neural networks and its applications", Elsevier Expert Systems with Applications 41 (2014) 3965–3974
17. Mariusz Paradowski, Mariusz Durak and Bartosz Broda, "Bag of words- quality issues of Near-Duplicate image retrieval", Machine Graphics and Vision, vol. 23, 83-96, 2014.
18. Masato Yonekawa and H. Kurokawa, "An automatic parameter adjustment method of pulse coupled neural networks" artificial neural networks, IC ANN 2009, vol. 5678, pp. 834-843 (2009).
19. Ondrej Chum, James Philbin and Andrew Zisserman "Near -Duplicate image detection using Min-Hash and tf -idf weighting", IEEE trans image processing 133-142 , vol. 6 (2006)
20. R. Eckhorn, H.J. Reitboeck, M. Arndt, P.W. Dicke "Feature linking via synchronization among distributed assemblies: Simulation of results from cat cortex, Neural Computation," NeuraComputation, Vol. 2, No. 3, pp. 293-307, fall 1990.
21. R. Eckhorn , H.J. Reitboeck, M. Arndt, and P.W. Dicke , " A neural network for feature linking via synchronus activity :Results from cat visual cortex and from simulations , "in Models of brain function, R.M.J. cotterill, Ed. Cambridge, U.K.: Cambridge univ. Press, 1989, pp. 255-272.
22. Raul C. Muresan, "Pattern recognition using pulse coupled neural networks and discrete Fourier transforms," Neurocomputing, Vol. 51, pp. 487-493, April 2003.
23. S. French and R. B. Stein, "A flexible neural analog using integrated circuits," IEEE Trans. Biomed. Eng, vol. BME-17, pp. 248–337, 1970.
24. Thomas Lindblad and Jason M. Kinser, "Image processing using pulse coupled neural networks" second revised edition ed.: springer, 2005.
25. Trong- Thuc Hoang, Ngoc-Hung Nguyen, Xuan-Thuan Nguyen and Trong- Tu Bui, " A Real - time Image Feature Extraction Using Pulse- Coupled Neural Network ", International Journal of Emerging Trends and Technology in Computer Science, Vol. 1 , Issue 3, September-October 2012.
26. Wei Dong, Zhe Vang, Moses Charikar and Kai Li , "High-Confidence Near-Duplicate image detection", ICMR hongkong china, pages 3304-3311, june 2012.
27. Wu Mingliang and Zhang gang, Huang Jiankang , Shi Yu, and Shao Ling. "Edge detection for alluminium alloy MIG Welding pool based on pulse coupled neural network," 7th international conference on natural computation (ICNC) vol. 2, pp. 691-694, 2011.
28. X. Gu, D. Yu, L. Zhang, "Image shadow removal using PCNN", IEEE Transactions on Neural Networks, 16 (3) (2005) 692-698.
29. Yonekawa Masato and H. Kurokawa, " An evaluation of the image recognition method using PCNN" artificial neural networks, IC ANN 2011, vol. 6791, pp. 217-224 (2011).
30. G. Kalaiarasi and K.K. Thyagarajan "Retrieval of Near Duplicate Images using K means and PSO Clustering" Indian Journal Of Science and Technology , Vol 9 (SI) DOI:10.17485, December 2016.