Pulse Coupled Neural Network based Near-Duplicate Detection of Images (PCNN – NDD)

Kandaswamy Kondampatti THYAGHARAJAN, Governor KALAIARASI
R.M.D. Engineering College, Anna University, Chennai, India
kkthyagharajan@rmd.ac.in, kalaiarasig@rmd.ac.in

***Abstract*—Near Duplicate images are variants of original image with some transformations / manipulations / forgeries in it. The illegal copies of images are identified to protect copyright enforcement and reduce redundancy. The existing works in ND detection are less accurate in the identification of similar images as near duplicates. Pulse Coupled Neural Network (PCNN) is found to be a suitable processor for all the image processing techniques including feature extraction. In this paper, PCNN is applied in the detection of near duplicate (ND) images. The proposed work Pulse Coupled Neural Network based Near Duplicate Detection of Images (PCNN-NDD) is a two-step process – (1) feature extraction using PCNN and (2) fast image similarity measurement using correlation coefficient. Our system is capable of improving the accuracy effectively. The advantage of the proposed work lies in the proper setting of PCNN parameters to identify the similar images. The experimental results show that our PCNN-NDD system enhances the detection results and improves the accuracy when compared to other traditional systems.**

***Index Terms*—computer vision, copyright protection, feature extraction, image processing, neural networks.**

I. Introduction

In this modern era, exposures to social network and in turn manipulations of images using the powerful image editing tools are increasing day-by-day. As a result, near duplicate images are created and uploaded on the Web. ND images are the minor variants of the original image which is a challenging task to detect. ND has many definitions in literature. ND images are images with variations due to digital editing operations such as geometric transformations, colour changing, compression, text addition, framing, and other non-affine geometric transformations. The commonly used transformations include geometric operations, blurring, noise contamination, enhancement and compression. In general ND image is a transformed or forged or pirated or altered or edited version of an original image. Many researchers have used bag-of-local features (BOF) to find the similarity between images [1-2]. The main drawback in these methods is the reduction in the ability to discriminate the images due to BOF quantization. Increasing the discriminating power makes the algorithm to omit some of the near-duplicate images and decreasing the discriminating power makes the algorithm to select some of the images which are not similar to the query image. In copy-move forgery, the original image is altered by image editing tools to get a tampered or forged image. It is very difficult to distinguish the original and tampered images as shown in fig. 1(a) and fig. 1(b). These images were taken from CoMoFoD dataset [3] which contains many original images and their forged images. All these forged images are near-duplicate images and they are not easily distinguishable from its original version. Our goal is to propose a methodology to detect all the forged near-duplicate images in a large corpus of images. We use standard copy-move forgery databases to evaluate our method. Even though we concentrate on copy-move forgery databases and hence copyright infringement detection [4], the same method is easily adopted for landmark identification [5] and commercial retrieval [6]. Near-duplicate forged image search is a challenging task because the variation is very small as both the original image and near-duplicate image looks visually similar. Qureshi et al. surveyed different forgery detection methods in [7] and highlighted that forgery detection is a challenging one when multiple manipulations / tampering are applied.

a) Original Image b) ND Image

Figure 1. Example of ND Image

The existence of these near duplicate images in the web image search indicates the presence of redundancy and represents violations of copyright. To improve the quality of user's search results, the near duplicate images should be identified [8-9] and the overhead of viewing the similar images should be avoided by grouping the ND images [10-12]. Thus, the ability of reliable and accurate identification of such variants allow the detection of copyright violations, detection of plagiarism, copy-move forgery detection, forgery identification in paintings and localizations of paintings. Near-duplicate detection (NDD) is also applied for effective photo management and browsing facilitating representative photo selection and region-of-interest determination [13]. Also, it avoids spreading illegal content over the internet and reduces redundancy during the presentation of image search results.

There are two main requirements in detecting near-duplicate images. One is speed which is important when NDD is used for information retrieval, the other one is detection effectiveness which is required when NDD is applied for forgery detection. To meet these requirements, a design of feature vector generator employing PCNN is presented for NDD in this paper. The image feature extraction system requires PCNN model to generate a feature vector by an iterative process. The time series of PCNN output is invariant to translation, scale, rotation,

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distortion and intensity [14]. PCNN-based features are used by researchers to characterize the regions of images which are invariant to scale, rotation [15], geometric transformation and photometric transformations. Since its invention by Eckhorn in 1990 [16], PCNN-based features view an image as a collection of pixels and it also considers the relationship of a pixel with its neighbouring pixels. It was introduced from the research of synchronous oscillation phenomenon in visual cortical neurons of cat in the case of external pulsing. The PCNN does not require any training and it produces minimal number of features even for large images. The main disadvantage of PCNN is the difficulty in estimating the optimum values for its large number of parameters. Another problem is to find out the optimal number of features to be generated.

The PCNN and its numerous variations are found to be useful in a wide variety of applications including smoothing, feature binding, edge and peak curvature extraction, image fusion, image decomposition, path optimisation, invariant feature generation, logical rule sets and impulse movement detection [17]. It is unique from other techniques due to its synchronous pulsed output, adjustable threshold and controllable parameters. The original PCNN was modified as unit linking PCNN (ULPCNN) and adaptive unit linking PCNN (AULPCNN) for a simple implementation, higher recognition and anti-noise disturbance [18] based on the application. The PCNN algorithm is noise resistive and robust against the translation, scale and rotation of the input patterns when compared to other image processing algorithms. However, the main drawback of PCNN is the high computing complexity for feature generation [19]. The estimation of parameters is done to a greater extent in our proposed PCNN-NDD system which is seen from the detection accuracy obtained. Also, the computing complexity for feature generation is reduced.

The remaining section of this paper is organised as - Section 2 reviews the feature extraction methods used for ND image detection and analyses the suitability and limitations of PCNN for NDD, Section 3 presents the overview of the proposed system, Section 4 discusses the results, performance analysis and comparison of the proposed system with the existing methods and finally the proposed work is concluded in Section 5.

II. RELATED WORKS

This section provides the outline of the various feature extraction methods used for Near Duplicate Detection (NDD). This section also analyses the suitability of PCNN and its limitations for NDD. Analysis shows that as of now, there is no existing quality work for detection of near-duplicate images using PCNN.

The problems of near-duplicate images attract the attention of a wide range of experts in the field of computer vision and content-based image retrieval due to lack of universal solutions. Near duplicates exist not only in images but also in video and music. Near duplicate identification/detection is used in various applications such as News Search, Topic Detection and Tracking, Copyright infringement, etc. Efficient near duplicate detection is motivated by two practical scenarios - finding copyrighted images and detecting forged images. Ke et al. used robust interest point detector and distinctive local descriptors to solve near duplicate and sub-image retrieval problem [20]. The method is highly resistant to common transforms but the system is very slow as the system needs to query more number of features at a time. Scalability of image and video databases is focused in [21] by using colour histogram and scale invariant feature transform (SIFT) descriptor. It could not detect if the viewpoint changes.

Scale Rotation Invariant Pattern Entropy (SR-PE) [22] along with PSIFT (PCA version of SIFT) matches the key point patterns when there are more than one ND regions with different transformations. SR-PE measures the spatial regularity of matching patterns formed by local key points. But SR-PE does not work well for viewpoint change and in localizing the near duplicate regions. The matching speed of detection method based on SIFT features is high. To improve the matching speed, Singular Value Decomposition (SVD) method is proposed in [23] for feature matching and extracts the new feature from the set of SIFT feature points. This SVD-SIFT feature reduces the time required to perform image matching and hence reduces the computational cost. But the position of SIFT feature points is not considered. Harris-Hessian feature detector is used to accelerate the local feature detection in [24]. It requires additional memory and is not effective for establishing correspondences between similar images. Zhang et al. proposed an edge based local descriptor called Edge-SIFT in [25]. The Edge-SIFT is built upon edge maps of local image patches and keeps track of both locations and orientations of edges. It is specific only to mobile search.

Lei et al. [26] proposed geometric invariant features based on Radon transform. The Radon feature is robust to rotation, scaling, compression, noise contamination, blurring, illumination modification, cropping, etc. But the extraction of feature is time consuming. ND image retrieval based on Bag-of-Visual words result in mismatches because of quantization errors of the local features. So, Yao et al. [27] designed a contextual descriptor to measure the contextual similarity of visual words in order to discard the mismatches present. Also, the discriminability of local features is improved. But it does not encode enough spatial information as it considers only local areas instead of considering the entire image, resulting in poor discriminability. Also, it is robust to image editing operations such as rotation, scaling and cropping except to perspective transformation of image. In [28], image is represented by a signature, the length of which varies on the number of patches in the image. The probabilistic center-symmetric local binary pattern visual descriptor is used to characterize the appearance of each image patch. The earth mover’s distance is used to compute the similarity between two signatures. It is high if there are more patches and the average time for signature generation is also high. Kim et al. [29] discovered near duplicates on one billion images to overcome scalability problem in the existing works. This method is implemented using Map Reduce framework and it takes about 17 hours of computation time on 1 billion images. In [30], classification of ND images using texture features and fuzzy support vector machine (SVM) was proposed. Gray level co-occurrence matrix (GLCM) was used to extract texture features in the paper. In [31], ND images are retrieved based on color and texture features. Particle Swarm Optimization based k-means clustering is used to retrieve images effectively.

A forged image is also one form of ND image. Gajananand Vijay [32] reviewed the different techniques used for image forgery detection. He classified various techniques used for image forgery detection and explained the steps involved in a general forgery detection system. But it does not provide any idea about PCNN-based image forgery detection system. To detect a forged image modified during copy-move attack, SIFT features are used [33]. The salient key points are not recovered by SIFT-like methods. Muhammad et al. proposed a blind copy move image forgery detection method using undecimated dyadic wavelet transform (DyWT) in [34] and it is shift invariant. In [35], detection performance is analyzed based on the whole image as well as on the pixel present in particular image. It performed well in small amounts of scaling. But it does not yield good results using larger scaling parameters and can only handle small degrees of rotation. The tampered inpainting images are recognized in [36] for the forgery detection. An inpainting image is constructed by changing the target area using the surrounding regions in the same image. Therefore, the key problem is recognizing the fake region and search for similar regions in the faked image. Copy-move forgeries are also detected by this method. This method is not capable in locating forged regions of small sizes. Also, if the forged region is from different source then it fails.

Cozzolino et al. proposed fast and accurate copy-move detection in [37]. The dense field technique is used for the accurate detection and localization of copy-move forgery based on rotation-invariant features. Since it is very slow, PatchMatch algorithm is used to produce performance improvements on localization, accuracy and speed. But the dense features fail to guarantee the invariance properties. A noise tolerant filter known as Correlation filter determines whether an original image has undergone any modifications [38]. Zhou et al. presented a global context verification scheme to filter false matches of copy detection in [39]. From the SIFT matches obtained between images based on Bag-of words (BoW) quantization, the overlapping region-based global context descriptor (OR-GCD) filter the false matches. This method achieves higher accuracy but low efficiency for partial-duplicate image detection. In [40], the forged region is distinguished from images having Similar but Genuine Objects (SGOs) by using spatial similarity metrics. The results show that the performance is degraded significantly in the images containing SGO. Xu et al. presented a fast method to detect forged images using SURF (Speed Up Robust Feature) descriptor [41]. This is invariant to rotation, scaling, etc. But it detects only certain transformations and post-processing methods. Aniket et al. [42] addressed the problem of forged images having SGO by using rotated local binary pattern (RLBP) based rotation-invariant texture features. This is better for complex tampering but not for all the manipulations.

On summarizing the literature's results, the present systems fail to produce good results when the duplicates are created by i) rotation, ii) larger scaling, iii) many simultaneous image manipulations and iv) change in the viewpoint. These systems also suffer from i) high computational complexity, ii) high false identification and iii) low accuracy.

To overcome the above issues, Pulse Coupled Neural Network is used in the ND image detection. PCNN is used for feature extraction process as it is simple and extracts reduced number of features. Many researchers work on PCNN for its easy implementation, higher recognition, anti-noise disturbance, robustness, etc. Raul C. Muresan proved that the maximum rotation error is obtained for the two principal diagonals (45º and 135º) in a pattern recognition method using discrete Fourier transform on the global pulse signal of a PCNN [43]. This rotation error is caused by pixel discretization (the diagonal of the pixel is $1\sqrt{2}$, so the diagonal distance between pixels is larger than the distance along the axes) [44]. In [19], the PCNN used for image recognition shows the binary images produced at various values of G(n). Euclidean metric is applied on Z(n) for classification of images. The recognition precision was estimated in percentage against the number of iterations used. Duplication arising due to rotation is identified with 100 % precision but more than 45% change in the texture could not be classified properly. Yuli Chen et al. [45] have proposed a biologically motivated region based PCNN method to recognize objects from complex real-world scenes. PCNN is used for feature extraction in many works [46-47]. The main aim of PCNN is to reduce the number of generated features and to determine the optimum number of iterations [48]. The existing problems in PCNN are i) there is no adaptive parameter setting and ii) the cause-effect relationship between parameter settings is very difficult to establish [49].

The limitations of PCNN are i) trial and error parameter setting and ii) Manual selection of the final results [50]. Therefore, to use PCNN as the most efficient, accurate and best feature extraction tool, appropriate parameter setting plays the major role. The parameter setting is done effectively in our proposed PCNN-NDD work.

III. PROPOSED SYSTEM

The overall flow of the proposed system is shown in fig. 2. Initially features are extracted using PCNN. Then similarity measure is calculated using Correlation Coefficient. Based on the correlation, ND image is detected.

A. The PCNN Model

Pulse Coupled Neural Networks are unsupervised and self-organizing network. The number of neurons in the network is equal to the number of input images. Each pixel in the image is connected to a unique neuron and each neuron is connected with surrounding neurons through linking field. A feeding field, a linking modulation and a pulse generator forms a neuron. The feeding field receives input signals from the neighbouring neurons and from external sources. The linking inputs have faster response time when compared to feeding connections. The biased and multiplied linking inputs are multiplied with the feeding input to produce the total internal activity U which is the Linking or Modulation part. Finally the pulse generator of the neuron consists of a step function generator and a threshold signal generator. The neurons in the network respond to stimuli which are known as firing. This firing is enabled when the internal activity of the neuron exceeds a certain threshold. The neuron output Y is set to 1. The output of the neuron is then iteratively fed back with a delay of single iteration. The output of the neuron is consequently reset to zero when the threshold is larger than the internal activity U. The PCNN neurons produce temporal series of pulse outputs after 'n' number of iterations. The pulse output carries information about the input image. Feeding and Linking input communicates with the neighbouring neurons through the synaptic weights M and W.

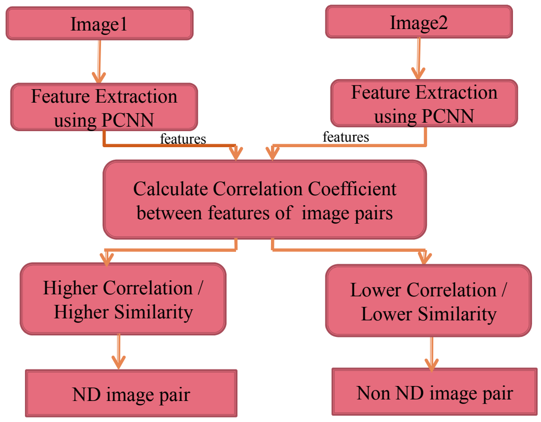

Figure 2. Overall Flow of the Proposed System

The basic structure of the PCNN neuron is shown in fig. 3. The indices (i,j) is the position of a neuron in the network and a pixel in the image The indices (k,l) represent the position of the surrounding neurons. The gray level of the input image pixel is given by S_{ij} and 'n' is the iterative step number. The $F_{ij}[n]$, $L_{ij}[n]$, $U_{ij}[n]$ and $T_{ij}[n]$ are the feeding input, linking input, internal activity and dynamic threshold respectively. There are four 1-iteration delay registers to store the respective current values and makes it available for the next iteration. The pulse output of a neuron at n^{th} iteration is $Y_{ij}[n]$ and it is equal to 1 if the neuron is activated.

The respective equations (1) - (5) are given as:

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

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

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

$$T_{ij}[n] = T_{ij}[n-1]e^{-\alpha_T} + V_T Y_{ij}[n] \quad (4)$$

$$Y_{ij}[n] = \begin{cases} 1, if U_{ij}[n] > T_{ij}[n] \\ 0, else \end{cases} \quad (5)$$

The $M_{ij,kl}$ and $W_{ij,kl}$ are constant weight functions. β is the linking coefficient constant and α_F, α_L and α_T are the attenuation time constants. V_F, V_L and V_T are the inherent voltage potentials of the feeding signal, linking signal and dynamic threshold, respectively. All the network pulses $Y_{ij}[n]$ form a binary image which contains important information such as region information, edge information and features of an object in the input image.

B. Feature Extraction using PCNN

The input image is transformed into a series of binary images. The binary image sequence contains a lot of information about the shape, edge and texture features of the original image. They can't be directly used as image feature since the information data is too big. We can carry out some transformation on these sequence images to extract a small amount of data as an original image feature. Johnson [17] first proposed time series as the image feature. The length of the feature vector depends on the total number of the PCNN iterative steps. In order to find the minor difference between the images, similarity measure is estimated.

The Correlation Coefficient (CC) is a relatively good criterion for determining the similarity between two feature vectors with the inherent ability to suppress noise. CC is also used in Image quality assessment [51], affine transformation recovery in digital watermark applications [52] and in stereo matching of colour images in micro stereovision [53]. In our PCNN-NDD method, CC is used to judge the degree of similarity between feature vectors of two images in percentage.

Suppose feature vectors of two images are $Z_{Al} = [Z_{A1}, Z_{A2}, .. Z_{AL}]$ and $Z_{Bl} = [Z_{B1}, Z_{B2}, .. Z_{BL}]$, respectively.

The Percentage of similarity (%S) is

$$S = \frac{\sum_{l=1}^{L} (Z_{Al} - \bar{Z}_A)(Z_{Bl} - \bar{Z}_B)}{\sqrt{\sum_{l=1}^{L} (Z_{Al} - \bar{Z}_A)^2 X (Z_{Bl} - \bar{Z}_B)^2}} X100 \quad (6)$$

where 'l' is the iteration number and 'L' is the total number of iterations, $\bar{Z}_A$ and $\bar{Z}_B$ indicate the mean of vector Z_A and Z_B respectively as shown below –

$$\bar{Z}_A = \frac{1}{L} \sum_{l=1}^{L} Z_{Al}\ ,\ \bar{Z}_B = \frac{1}{L} \sum_{l=1}^{L} Z_{Bl} \quad (7)$$

The Correlation Coefficient (CC) and Percentage of Similarity (%S) are not same measures. In our method, Correlation Coefficient (CC) measure is used to compute the percentage of similarity (%S). Correlation coefficients are computed as values between +1 and -1. Positive correlation means both the images are highly similar to each other whereas negative correlation means there is no similarity between the two images. Both the positive and negative correlations are two extremes. If CC is closer to the absolute value 1, then the correlation of the two feature vectors is more resulting in higher similarity between two images. If CC is closer to 0, then the similarity between the two images is very low. If CC is closer to '-1', then the two images are completely different with no similarity. We get similarity value 1 if an image is compared to itself. We found that the optimum threshold value was 0.94 based on the experiment we conducted to compare two images i.e. only if the correlation coefficient between two images is in the range from 0.94 to 1.00, the image is considered as ND image. Hence there is no question of other lower values and negative values. They are not considered because these values are not produced by near duplicate images. This approach not only greatly reduces computing cost, but also improves the image retrieval speed.

C. Algorithm

The proposed work algorithm is presented in this section -

```
PCNN based NDD algorithm - To compute
correlation percentage (%S) between two images
Input: Images – IA and IB
Output: % of similarity between IA and IB
   Read IA
   [Rowsize, Colsize] ← Size (IA)
   Set PCNN parameters←[aF aL aT vF vL vT β]
   Compute {ZAl}←PCNN (IA, parameters, No. of
                      Iterations, immean)
   Repeat above steps for IB
   Compute {ZBl}←PCNN (IB, parameters, No. of
                      Iterations, immean)
   Compute Similarity %S
   Compare %S and %Threshold
   Return ND or non ND
```

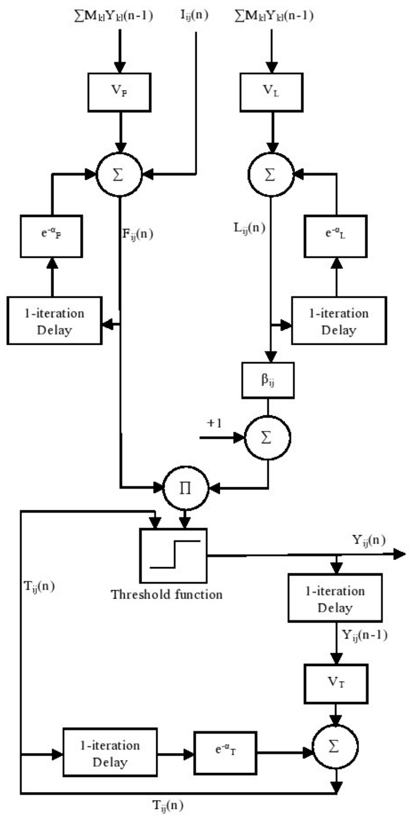

Figure 3. Basic structure of PCNN neuron

```
Feature Extraction Algorithm using PCNN
Input: Image I, Parameters, No. of Iterations
and mean (mean of Image)
Output: Features / (Z Values) of image I
   PCNN (I, Parameters, No. of Iterations,
     immean)
   Initialize PCNN parameters
   Assign 0 for deltathresh, G, Mweightsum,
                Lweightsum
   for k = 1:Rowsize
   for l = 1:Colsize
   Compute Mweightsum←Mweightsum + M(k,l)*Y(k,l)
   Compute Lweightsum←Lweightsum + W(k,l)*Y(k,l)
   end for
   end for
   for k = 1:Rowsize
   for l = 1:Colsize
   Compute F, L, U, T
   Find deltathresh ← U - T
   If deltathresh>0
     then Y ← 1  else Y ← 0
   end if
   Compute G
   end for
   end for
   Compute Z
   return Z
```

D. Parameters of PCNN

The determination of PCNN parameters greatly increases the performance and the flexibility in handling different images [54]. This is the most important step in our work. The coefficient β is an important parameter because it can vary the linking strength of neurons. Generally, larger β encourages low brightness neuron to fire and smaller β decreases the ability to capture neighbouring neurons and maintains a high similarity in the fired region. Larger α_T decreases the running time of PCNN. The v_T decides the threshold value of fired neurons. If the value of α_F is larger, it causes a faster decay of the feeding channel. The parameter v_F enlarges or reduces the influence from surrounding neurons based on its value [55]. Yuli Chen et al. attempted to determine the values of the parameters by establishing associations between the properties of neurons and the properties of input images [56]. Their method does not require trials or prior training. Finding appropriate values for the parameters is a serious problem and it requires manual adjustments or heavy training. Kuntimad and Ranganath determined the minimum and maximum values of β for object segmentation based on intensity ranges of objects and background [57]. Stewart et al. in [58] proposed region growing PCNN in which the dynamic threshold and β are manually set with incremental constants. Bi et al. [59] determined weight matrices and β adaptively according to spatial characteristics. Yonekawa et al. [60] automatically adjusted W,β,α_T, with many trials. Berg et al. [61] and Ma et al. [62] set all parameters automatically but with many trials. Papers [63-64] used 37 iterations but how did they choose was not explained. If M_{kl} is omitted, the neuron with input $I_{ij} = 0$ produces only 0 as output in all iterations and it does not influence other neurons. But, in papers [54], [65–66], this is set to zero. In our paper, the weight values are set as $M_{ij,,kl} = I_{ij} - \bar{x}$. The $\bar{x}$ is the mean intensity value of image pixels. The PCNN shows an improvement in its performance at 45^0 and 135^0 rotation.

In [50], the authors chose flexible threshold decay constant by α_T = Constant / mean value of image pixels. This is because a lower value of decay constant for high intensity images or image areas is needed. In these images the mean value of pixels is high and lower threshold decay constant increases the threshold value of the high intensity pixels. α_F is not used in the model. Adaptation based on intensity level is made with α_F. But in this case α_T is made directly proportional to the mean of the image and it is chosen as $\alpha_T = \alpha_F$. If the intensity of the image has increased due to forgery, F_{ij} decreases to nullify this forgery action. This threshold value is decreased proportionately. The increase in the mean value makes the threshold value to decrease at a faster rate so that same output is produced by the both original and duplicate image. This provides better result in forgery identification.

In many research works [55], [65-68] same values of PCNN parameters are used to process all the images. Here the parameters are set in advance as shown in the Table I. L,U and Y matrices are initially set to zero and Connection

Matrix W and M [67],[69] is given by [0.5,1,0.5;1,0,1;0.5,1,0.5].

TABLE I. PARAMETERS OF PCNN

Parameters	α_F	α_L	α_T	V_F	V_L	V_T	B
Yide Ma et al. [67]	0.1	1.0	1.0	0.5	0.2	20	0.1
Zhaobin Wang et al. [69]	$\propto$	0.1	0.2	0	0.2	20	0.1

It does not provide good results for many images. Also, there is no particular method to follow in the works for the parameter setting. So, based on the parameters set in [49, 67], COVERAGE [40] database is tested and the accuracy is around 50% which is very less when compared to the previous works. To improve the accuracy, the parameters are set adaptively based on its statistical characteristics 'mean', which is the average values of all pixel intensities and is denoted as immean. By choosing mean as the parameter, even a minute difference in the image is detected. The parameters are set as follows -

$a_F \leftarrow$ immean;
$a_L \leftarrow 2*$immean;
$a_T \leftarrow$ immean
$v_F \leftarrow$ immean / (Rowsize * Colsize)
$v_L \leftarrow$ (100*immean) / (Rowsize * Colsize)
$v_T \leftarrow 10*$immean;
$\beta \leftarrow 0.1*$immean

The U and Y matrices are initially set to zero; M is assigned to I – immean; L and W are set to ones and T is set to the mean value of the image.

IV. EXPERIMENTS

The performance of the proposed method is studied with respect to number of features selected and the threshold is fixed to calculate the similarity between two sets of features. Similarly deciding the values for PCNN is a challenge because it depends on the application. As a result it was decided to conduct a series of experiments. The first experiment was conducted to fix the PCNN parameters by choosing more number of PCNN features to avoid detecting some of the near-duplicate images. But at the same time choosing less number of PCNN features causes the non near-duplicate images being selected as near-duplicates. Therefore choosing the suitable number of features depends on the datasets which are searched for NDs. Analysing the suitable number of features and a threshold using a large database is difficult. Series of experiments are performed to justify the performance of the method and parameter selection in comparison to other existing approaches. All experiments are conducted on Intel (R) Core (TM) i5 CPU M 460 @ 2.53 GHz with 4 GB RAM and was implemented using MATLAB V2015.

A. Determining optimum threshold and optimum number of features

Two datasets CoMoFoD dataset [3] and COVERAGE dataset are used [40]. The CoMoFoD database has been organized into 2 main categories according to the image size: 200 small images with resolution 512X512 pixels (taken for our analysis) and 60 large images with resolution of 3000X2000 pixels. The first original image found in the CoMoFoD is shown in fig. 4 (a). The forged versions of this image is given in fig. 4 (b), 4 (c) and 4 (d) which is obtained by performing manipulation. The forged version fig. 4 (b) is subjected to the following post processing methods to derive many more duplicate images and to make the forgery perfect - Brightness Change (BC), Contrast adjustment (CA), Colour reduction (CR), Image blurring (IB), JPEG compression (JC), Noise addition (NA). There are four more image manipulation categories such as rotation, scaling, distortion and combination wherein each image has undergone postprocessing methods resulting in almost 10,000 images in this dataset.

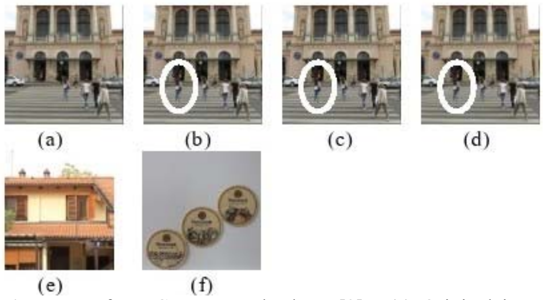

Figure 4. Images from CoMoFoD database [3] - (a) Original image, (b) forged image, (c) JPEG Compressed – 50% quality of (b), (d) blurred image of (b), (e) – (f) other images

The precision and recall are calculated using the formula (8) - (9). Precision determines the ability to exclude false positives whereas recall measures the accuracy of retrieving near-duplicates.

The precision of a system is defined as the ratio of number of correctly selected ND images to the number of correctly selected ND images and number of images wrongly selected as ND.

$$\%\text{Precision}= \frac{TP}{TP+FP} \text{ x } 100\ \% \tag{8}$$

The recall of the system is defined as the ratio of number of correctly selected ND images to the number of correctly selected ND images and number of wrongly omitted ND images.

$$\%\text{Recall}= \frac{TP}{TP+FN} \text{ x } 100\ \% \tag{9}$$

where TP is True Positive, FP is False Positive and FN is False Negative.

The values of precision and recall with respect to threshold for various iterations are plotted in the fig. 5 for CoMoFoD database. The curve precision-10 indicates how the precision value changes with respect to the matching accuracy (threshold) when the number of features extracted is 10. We understood that the precision increases with threshold values because at high threshold values false positives are reduced. This is required in large databases. But at the same time true positives also get reduced. If the number of PCNN features used is high, then the precision is almost constant and it reaches a maximum value. But, using more number of PCNN features reduces the recall, because it increases the false negatives. We observe that when the number of PCNN features is between 30 and 50 and threshold value is between 0.93 and 0.95, we get values for both precision and recall significantly high. Hence we frame the following heuristic rule for selecting the number of PCNN features and the threshold value (matching accuracy).

Heuristic rules,

30 < Number of PCNN features < 50

0.93 < Threshold Value < 0.95

This may slightly change depending on the database.

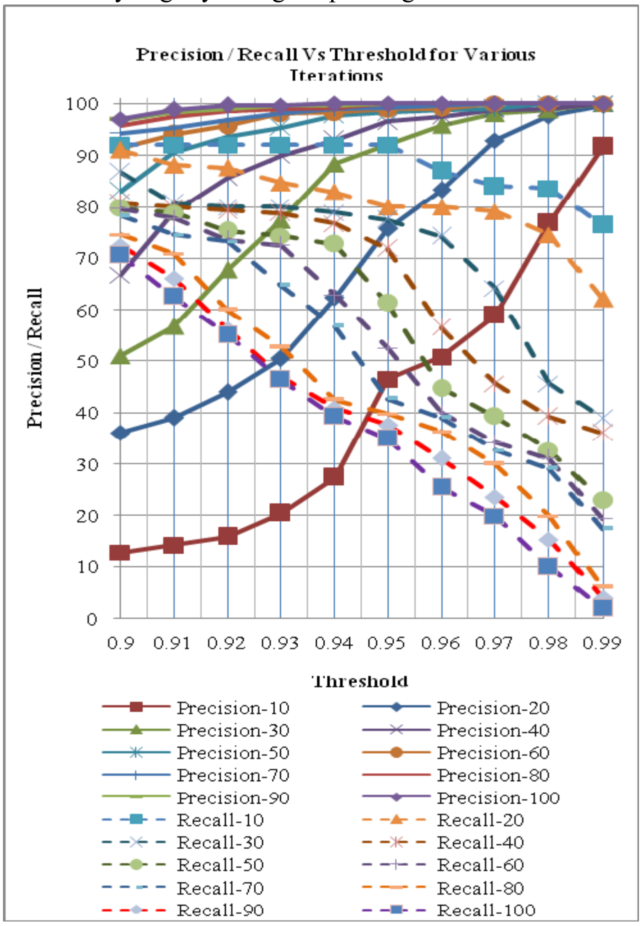

Figure 5. PR-Curve vs Threshold for various iterations in CoMoFoD database

Generally a perfect precision score of 1.0 (100%) means that every result retrieved by a search is relevant; but does not say anything about whether all the relevant documents are retrieved. Whereas a perfect recall score 1.0 means that all relevant documents are retrieved by the search but does not say anything about how many irrelevant documents were also retrieved. F-measure combines both precision and recall in a single value. It is a measure of test's accuracy and reaches its best value at 1 (perfect precision and recall) and worst at 0. F-measure is calculated using the formula (10).

$$\text{F-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

At lower values of marching accuracies, the F-measure increases at a faster rate when the number of PCNN features chosen is between 10 and 20 as shown in fig. 6. When the number of features is between 30 and 50, the rate of increase in F-measure is less and above 50 numbers of PCNN features F-measure is almost constant. At higher values of matching accuracies, F-measure decreases at a faster rate.

Fig. 7 zooms the F-measure graph for features 30 to 50; we observe that the F-measure value is almost same at matching accuracy of 0.94 for PCNN features 30 to 50. So, we decide to choose a matching accuracy of 0.94 and number of PCNN features to 40 to get optimum values of precision and recall. We follow the heuristic rule given below for further investigation.

Heuristic rule:

Choose the number of PCNN features to 40

Choose the threshold value of 0.94

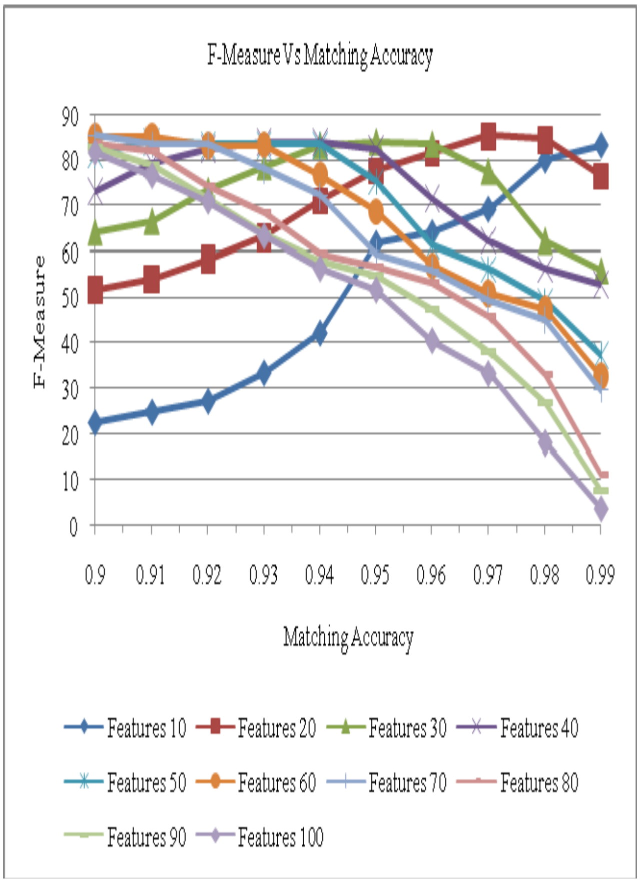

Figure 6. F-Measure Vs Matching Accuracy for CoMoFoD database

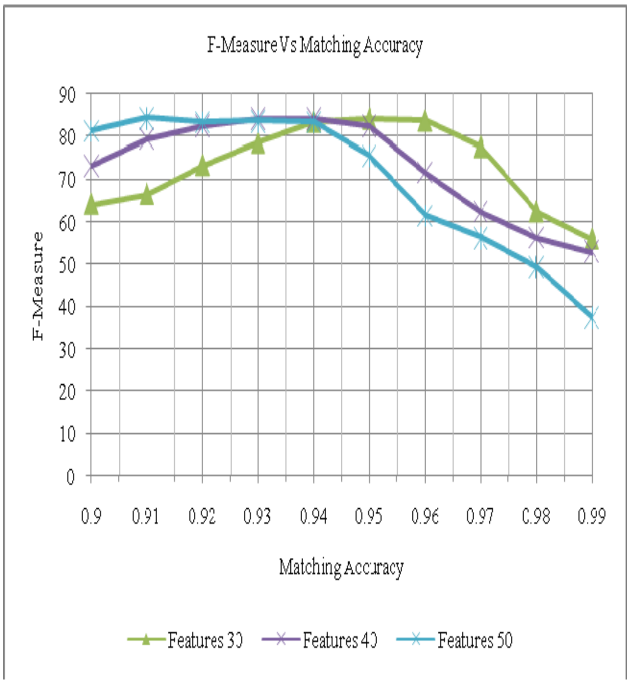

Figure 7. F-Measure Vs Matching Accuracy for Number of Features (30, 40, 50) for CoMoFoD database

To validate our matching accuracy (94%) and number of iterations (40), the performance of our PCNN-NDD method with these values are tested in standard databases such as

COVERAGE (COpy-moVe forgERy dAtabase with similar but Genuine objEcts) and CoMoFoD (Copy Move Forgery Detection) databases and is compared with the performances of other existing methods. The COVERAGE database contains 100 original images and 100 forged images. In this database, the forged / near duplicate images are obtained by performing transformations such as Translation, Scaling, Rotation, Free-Form, Illumination and Combination. Out of 100 near duplicate images, 16 images falls under translation transformation, 16 images under scaling, 16 images under rotation, 16 images under free-form, 16 images under illumination and 20 images under combination transformation.

Fig. 8 consists of sample images – the first pair is for the rotation, then scaling, translation, illumination, free-form and combination transformation correspondingly. The features of all the images in the dataset are extracted using PCNN algorithm and the percentage of similarity is computed. When the percentage similarity was set to 94%, our system recognizes the ND images in this database with 100% precision and 100% recall in many cases as shown in Table II. Similarly, Table III shows the values of precision and recall of CoMoFoD database for the same matching accuracy (94%) and number of iterations (40).

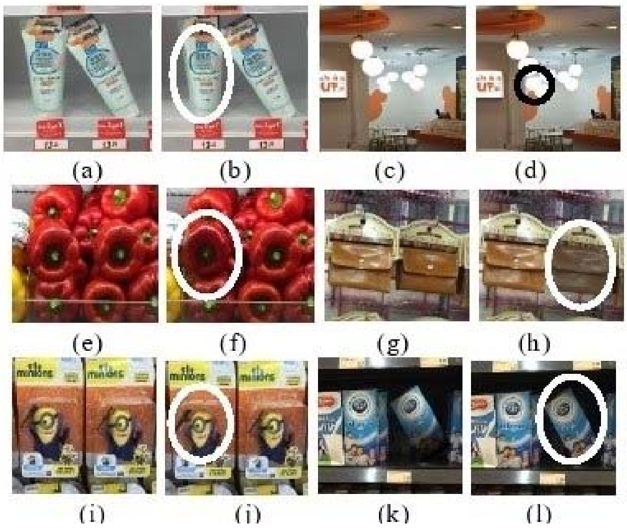

Figure 8. Sample Near Duplicate Image Pairs from COVERAGE database [40] – (a) Original image, (b) forged(rotation) image of (a), (c) Original image, (d) forged(scaling) image of (c), (e) Original image, (f) forged(translation) image of (e), (g) Original image, (h) forged (illumination) image of (g), (i) Original image, (j) forged(free-form) image of (i), (k) Original image, (l) forged(combination) image of (k)

TABLE II. PRECISION AND RECALL VALUES OF COVERAGE DATABASE

Image Transformation	Precision in %	Recall in %
Translation (16)	100	100
Scaling (16)	100	100
Rotation (16)	100	100
Free-Form (16)	100	50
Illumination (16)	100	100
Combination (20)	100	100
All(100)	100	91.67

Accuracy is not an appropriate performance measure for near duplicate detection of images. In most of the cases, over 99.9% of the images are not in the relevant category because of the large number of other images present along with the near-duplicate images. Even if the system provides maximum accuracy for a database that contains most of the images as relevant (positive cases), the same system may provide less accuracy when more images are added in the database that are not relevant because this may increase false positives. So the size of the database will also affect accuracy. Generally, we would expect a good search engine to display the search results images to be relevant to the query i.e. high precision. But, intelligence analysts are very concerned in yielding high recall. To consider both precision and recall, F-measure is computed which is nothing but a weighted harmonic mean of precision and recall. In our method, F-measure is chosen as the detection accuracy of near duplicate image detection and the average accuracy of our system for both COVERAGE and CoMoFoD are combined together and compared with existing methods and is presented in Table IV.

TABLE III. PRECISION AND RECALL VALUES OF COMOFOD DATABASE

Image Transformation	Precision in %	Recall in %
Translation (40)	88.4	76
Scaling (40)	100	76.4
Rotation (40)	89.7	10
Distortion (40)	100	77
Combination (40)	56	83
All(200)	93	77

TABLE IV. DETECTION ACCURACY OF PROPOSED SYSTEM WITH EXISTING METHODS SIFT, SURF, DENSE FIELD [40], SGO [42]

Image Transformation	Detection Methods				
	SIFT	SURF	Dense Field	SGO	Proposed System (PCNN)
COVERAGE	50.5	58.6	71.8	73	94.4
CoMoFoD	77	51.5	72	70.1	84.1

Wen et al. in [40] and Aniket et al. in [42] have compared detection accuracy of COVERAGE and CoMoFoD database using the methods such as SIFT, SURF, Dense Field and Similar but Genuine Objects (SGOs). It is concluded that i) SURF based detection accuracy is generally poor for both datasets and ii) The SIFT, SGO and dense-field methods perform better. Our proposed system is compared with these methods and it is proved that our system outperforms the existing methods resulting in best accuracy and is shown in Table IV.

V. CONCLUSION

We have presented a method for the detection of near duplicate images in an efficient way. To make NDD more accurate Pulse Coupled Neural Network is used for feature extraction and correlation coefficient was computed to find how the images are correlated with each other. Results show that the proposed PCNN-NDD system yields higher accuracy around 94.4% (that is more than 20% than other existing methods) in the detection of ND images. The number of iterations in our system has been chosen to be 40 such that time complexity is reduced and the matching accuracy of 94% is recommended to be set to maximize the precision and recall. However, the system finds little difficulty in detecting images that are blurred or rotated. This is done by excluding the new white pixels in the image added after the manipulation while computing the mean. The average run time of detection of near-duplicate images is 83 seconds with Intel Core i5, 2.3 GHz Processor used. The PCNN-NDD method was not tested with the images on the Internet. The system can be extended to detect blurred and rotated images successfully and optimal number of iterations to be used can be derived and tested with the images on the Internet in future work.

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