International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimization of Copy Move Forgery Detection with Region Selection Based on Domain Specific Characteristics

Shashikala S.[1], Ravi Kumar G. K.[2]

Submitted: 10/05/2023 **Revised**: 15/07/2023 **Accepted**: 07/08/2023

Abstract: Tampering and counterfeiting of digital images for various malicious purposes has become easier with advanced image editing tools. Copy move counterfeiting is a common image tampering technique created by copying a slice from one place to another in a image. Occlusion and partial distortions make counterfeit detection a challenge. To address it a deep learning signature approach was proposed in our earlier work. Though the accuracy of detection was high, the computational complexity was higher in that approach. This work proposes a novel region selection based optimization for reducing the computation complexity in deep learning signature approach for copy move forgery detection. The proposed region selection algorithm models the regions based on domain characteristics using a fuzzy Gaussian membership function. The proposed region selection optimization is able to reduce the computational complexity by 10% without compromising on accuracy of copy move forgery detection.

Keywords: *copy move forgery, region selection optimization, deep learning signature, partially occluded counterfeit*

1. Introduction

Digital image is a spatial representation of two or three dimensional scene. The visual impact it creates is higher compared to text and audio. Digital image processing has important in various applications like medical diagnosis, remote sensing, computer vision, video processing and pattern recognition etc. Images has also became a language independent mechanism for communication and news broadcast. Use of images in various applications also carries a risk of image manipulation for various malicious intensions. Introducing errors in medical diagnosis, defaming people, diverting criminal forensics, disrupting social harmony are some of malicious intension for which the attackers manipulate the images [1-3]. It has become very difficult to detect these image manipulations, as these manipulations can be done in a sophisticated manner using recent image editing tools. With availability of deep learning techniques, image counterfeit can be created with close resemblance to natural images. Copy move is one of the important image manipulation techniques where a region of image is copied to another region. The existing methods for copy-move tampering detection can be categorized to three types: frequency based, spatial based and hybrid. Frequency analysis and wavelet feature analysis are used in frequency-based techniques to detect tampering. based techniques to detect tampering. A major problem in existing techniques for copy move tampering detection is that their detection accuracy reduces in presence of partial occlusions. In our earlier work, a deep learning signature-based method was proposed to solve this problem. But the computational complexity is higher in this approach as the image is split into multiple non-overlapping blocks and computing deep learning signature for each block. Due to use of multiple blocks for signature computation and comparison, the computational complexity is higher in this approach. This complexity is reduced using region selection optimization in this work.

This work proposes a region selection optimization based on domain specific characteristics of image. A fuzzy Gaussian membership function is built to classify the regions in the image for lookup of copy move forgery detection. Deep learning signatures are extracted and matched only in the regions selected by the fuzzy Gaussian membership function. Due to this region selection optimization, the computational complexity of deep learning-based copy move forgery detection is reduced without compromising on detection accuracy. The contributions of this research work are as follows

(i) Modified active net based segmentation to segment only the regions which have high probability of being detected as copy move by optimizing the fitness function of TAN segmentation to deform based on shape.

(i) A novel fuzzy Gaussian membership function to select the regions for copy move forgery detection using domain specific characteristics of the image. The region selection has reduced the computational complexity of copy move forgery detection without compromising the detection accuracy.

(ii) Capturing the domain specific characteristics by splitting region to mesh and computing variance of mesh

[1]*Research Scholar, Department of Computer Science and Engineering, BGS Institute of Technology, Visvesvaraya Technological University, Belagavi, Karnataka, India*

[2]*Department of Computer Science and Engineering, BGS College of Engineering and Technology, Bengaluru, Visvesvaraya Technological University, Belagavi, Karnataka, India*

Email: shashiresearch.2021@gmail.com

segments and calculating K larger partial sum of variances for region.

Sections organization of this paper is as follows. Section 2 presents the survey on capture move forgery detection techniques and research gaps in them. Section 3 provides the proposed region selection-based optimization for copy move forgery detection. Section 4 presents the results of proposed optimization and comparison to existing works. Section 5 present the conclusion and future scope of work.

2. Survey

Li et al [4] selected the region for tampering detection using statistical features. A tampering probability map is constructed by splitting the image into blocks and selecting the blocks based on statistical features. The technique fails to detect copy regions in presence of occlusions and the approach does not optimize the number of regions. Y.Li et al [5] extracted scale invariant features in whole of image and matched it block by block across image to detect copy move forgery. Even for minor distortions, the approach fails to detect the match. Also computational complexity is high due to matching all the regions in the image. Mayer et al [6] split the image to grids and matched the lateral chromatic aberration between grids to detect copy move forging. The approach provides higher accuracy only for large number of grids which increases the computational complexity. Also the approach works only certain backgrounds. Bi et al [7] split the image to grids, extracted texture features and used offset guided searching to detect copy move forgery. Even minor transformations during copy move tampering reduces the accuracy of detection in this method. Wang et al [8] segmented images using super pixel segmentation algorithm and extracted key points from the segmented regions. Key point matching between regions is done to detect copy more forgery detection. The method could not detect copies in presence of occlusions. Teerakanok et al [9] split the image to grid and for each grid regions SURF and GLCM features are extracted. Grids are matched to detect copy move forgery. The method could not accommodate transformations and occlusions. Chou et al [10] split the image to blocks and extracted Gabor filter features from it. Matching is done across blocks to detect copy. This method is not resilient even for a small shape distortion. Chen et al [11] proposed a copy move detection algorithm based on Zernike moments (ZM). ZM features extracted from images in circular patches are matched to detect copy. In presence of occlusions, this solution fails to detect the copy due to high variance in ZM features between the images. Further this method does not rotational forgeries. Emam et al [12] split image to blocks. For each block, keypoints were located and histogram features were extracted from it. Matching is done block by block to detect forged regions, due to which computational complexity is higher. Thajeel et al [13] proposed a copy move detection algorithm based on Quaternion coefficients (QC). QC features of each block of image are compared using KD-tree to detect the coped regions. The computation complexity is higher and the solution is not resilient to occlusions in this approach. Mahmood et al [14] split image to non-overlapping blocks and extracted wavelet transform features from each blocks. Matching is done block by block to detect copied blocks. Object transformations can make this method erroneous. Hosny et al [15] extracted exponential transform coefficients from object segments of image. Segment similarity is measured with Euclidean distance. But the method is not transformation invariant and computational complexity increases with number of objects. Islam et al [16] split image to non-overlapping image blocks and extracted a hybrid feature combining discrete cosine transform (DCT) with local binary pattern (LBP). Matching of feature is done block by block to detect copied blocks. The hybrid feature is not transformation invariant. Cristin et al [17] proposed a copy detection mechanism specific to face. Faces in image are segmented and hybrid feature combining Gabor filter, wavelet and texture operator is extracted. The faces are matched using the hybrid feature using support vector machine (SVM) classifier to detect copy. The features are not resilient to occlusions. Bappy et al [18] used long short term memory (LSTM) for copy move forgery detection. Image is split to regions. Spatial maps are extracted for each region. LSTM classifier takes the sequence of spatial maps as input to detect copies. Presence of occlusions makes this method erroneous. Liu et al [19] segmented image into regions and extracted convolutional neural network (CNN) features from each region. Matching is done region by region to detect copy move forgery. Computational complexity is higher for extracting CNN features from each region. Khayeat et al [19] split image to regions and extracted Haar wavelet features from regions. Regions are compared for similarity using deep learning classifier. But the computational complexity is higher with Segnet deep learning classifier.

3. Proposed Solution

The working of proposed copy move forgery detection system is illustrated in Figure 1. The objective of the proposed solution is to reduce the computational complexity of copy move detection without compromising on detection accuracy in presence of partial occlusions. This objective is achieved by copy. In presence of occlusions, this solution fails to detect the copy due to high variance in ZM features between the images. Further this method does not rotational forgeries. Emam et al [12] split image to blocks. For each block, keypoints were located and histogram features were extracted from it. Matching is done block by block to detect forged regions, due to which computational complexity is higher. Thajeel et al [13] proposed a copy move detection algorithm based on Quaternion coefficients (QC). QC features of each block of image are compared using KD-tree to detect the coped regions. The computation complexity is higher and the solution is not resilient to occlusions in this approach. Mahmood et al [14] split image to non-overlapping blocks and extracted wavelet transform features from each blocks. Matching is done block by block to detect copied blocks. Object transformations can make this method erroneous. Hosny et al [15] extracted exponential transform coefficients from object segments of image. Segment similarity is measured with Euclidean distance. But the method is not transformation invariant and computational complexity increases with number of objects. Islam et al [16] split image to non overlapping image blocks and extracted a hybrid feature combining discrete cosine transform (DCT) with local binary pattern (LBP). Matching of feature is done block by block to detect copied blocks. The hybrid feature is not transformation invariant. Cristin et al [17] proposed a copy detection mechanism specific to face. Faces in image are segmented and hybrid feature combining Gabor filter, wavelet and texture operator is extracted. The faces are matched using the hybrid feature using support vector machine (SVM) classifier to detect copy. The features are not resilient to occlusions. Bappy et al [18] used long short term memory (LSTM) for copy move forgery detection. Image is split to regions. Spatial maps are extracted for each region. LSTM classifier takes the sequence of spatial maps as input to detect copies. Presence of occlusions makes this method erroneous. Liu et al [19] segmented image into regions and extracted convolutional neural network (CNN) features from each region. Matching is done region by region to detect copy move forgery. Computational complexity is higher for extracting CNN features from each region. Khayeat et al [19] split image to regions and extracted Haar wavelet features from regions. Regions are compared for similarity using deep learning classifier. But the computational complexity is higher with Segnet deep learning classifier selecting the region for copy move detection in two stages. In first stage, regions with characteristics shapes are alone segmented

using modified activenet segmentation. In the second stage, regions probable for certain domain are alone retained and other dropped. Deep learning signature based copy move forgery detection is trigged on the probable regions provided by the region selection.

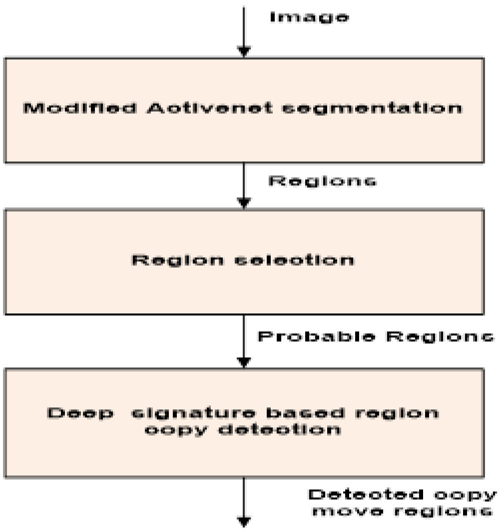

Fig. 1. Architecture of proposed optimized copy move detection

The proposed solution has three important stages. (i) Modified active segmentation to segment regions, (ii) region selection to filter un-necessary regions and provide probable regions for matching and (iii) Deep signature based region copy move detection. Each of these stages is detailed in below subsections.

A. Modified activenet segmentation

The input image is processed with modified activenet segmentation to identify regions of interest. Active net segmentation is a kind of Deformable model. Deformable models (DM) [24] are the surfaces and curves placed over images and the surfaces deform under influence of forces. The deformation can be due to forces both internal and external. Internal forces maintain the smoothness and external forces maintain the orientation towards the object of interest. Over the years many different version of deformable models have been proposed and one of noteworthy geometric deformable model is Topological Active Net (TAN) [25]. It is based on the concept of elastic two dimensional mesh. The deformation of mesh is controlled by a energy function and links are deformed where energy function achieving the minimal value. Thus the image segmentation is solved as energy minimization problem over the mesh defined as

$$v(a,b) = \big(x(a,b), y(a,b)\big) \quad (1)$$

where $(a,b)\varepsilon[[0,1]X[0,1]]$

The energy function controlling the mesh deformation is given as

$$E(v(a,b)) = \int_0^1\int_0^1 [E_{int}(v(a,b)) + E_{ext}(v(a,b))]dmdn \qquad (2)$$

In the above equation, E_int is the internal energy function which control the contraction and bending in mesh. It is calculated as

$$E_{int}(v(a,b)) = \alpha(|v_a(a,b)|^2+|v_b(a,b)|^2) + \beta(|v_{aa}(a,b)|^2 + |v_{ab}(a,b)|^2) + |v_{bb}(a,b)|^2) \qquad (3)$$

The subscripts in the above equation represent the partial derivates. $|v_a(a,b)|^2$ and $|v_b(a,b)|^2$represents the first order derivatives and they are calculated as

$$|v_a(a,b)|^2 = [\,||d_a^+(a,b)||^2 + ||d_a^-(a,b)||^2]/2 \qquad (4)$$

$$|v_b(a,b)|^2 = [\,||d_b^+(a,b)||^2 + ||d_b^-(a,b)||^2]/2 \qquad (5)$$

In the above equation d+ represents the forward difference and d- represents the backward difference. The are calculated as below

$$d_r^+(a,b) = [v(a+k,s) - v(a,b)]/k \qquad (6)$$

$$d_r^-(a,b) = [v(a,b) - v(a-k,n)]/k \qquad (7)$$

$$d_s^+(a,b) = [v(a,b+l) - v(a,b)]/l \qquad (8)$$

$$d_s^-(a,b) = [v(a,b) - v(a,b-l)]/l \qquad (9)$$

$v_{ab}(a,b)$ and $v_{bb}(a,b)$ are the second order derivatives and they are calculated as

$$v_{aa}(a,b) = \frac{v(a-k,b)-2v(a,b)+v(a+k,b)}{k^2} \qquad (10)$$

$$v_{bb}(a,b) = \frac{v(a,b-l)-2v(a,b)+v(a,b+l)}{l^2} \qquad (11)$$

$$v_{mn}(a,b) = \frac{v(a-k,b)-v(a-k,b+l)-v(a,b)+v(a,b+l)}{kl} \qquad (12)$$

The external energy is calculated in terms of intensity function as

$$E_{ext}(v(a,b)) = \omega f[I(v(a,b))] + \frac{\rho}{|N(a,b)|}\sum_{p\varepsilon N(a,b)} \frac{1}{||v(a,b)-v(p)||} f[I(v(p))] \qquad (13)$$

In the above equation I represent the intensity of pixel and N represents the neighborhood of pixel. The function f in above equation is calculated as

$$f[I(v(a,b))] = \begin{cases} Imax - \frac{\gamma\,\overrightarrow{I(v(a,b))}}{\overrightarrow{I(v(a,b))+}} \end{cases} + \varepsilon(Gmax - -G(v(a,b)))+\Phi GD(v(a,b)) \qquad (14)$$

In the above equation, Imax represents the maximum intensity value of pixel in the image and Gmax represents the maximum intensity of gradient image.

In TAN segmentation, a mesh is placed over the entire image and energy minimization is applied over each of links, to decide where the mesh is to be deformed by removing the link or retaining the link. There are multiple combinations of links that can be removed and best combination is found using greedy search. Energy function is calculated in each iteration and mesh is deformed. Iteration is stopped when no further links can be removed from the mesh.

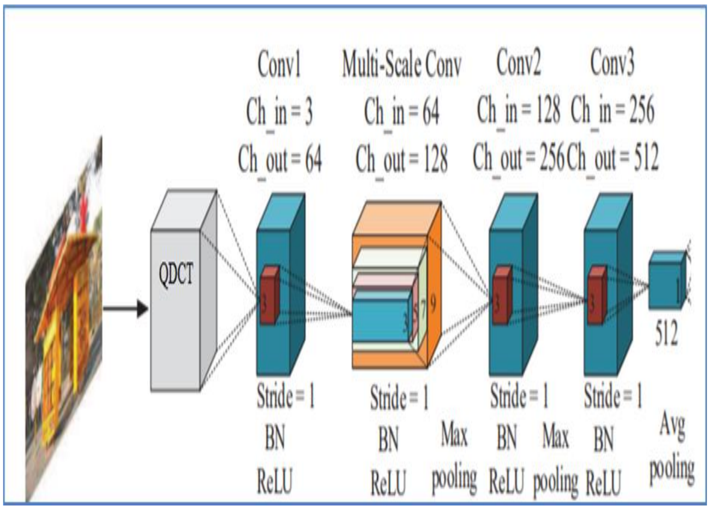

Fig. 2. Deep signature extraction

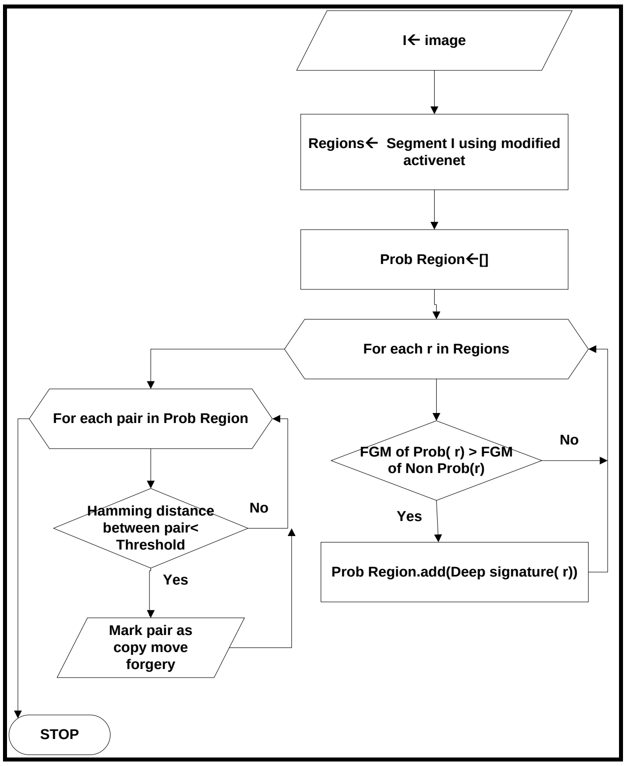

Fig. 3. Optimized copy move detection flow

The TAN segmentation is modified to select only regions with characteristic shapes. This is achieved by extended with a shape fitting based optimization function instead of intensity based fitting function used in TAN (eq.14). By this way deformation does not occur in area where there is no characteristics shape, eventually there are not segmented.

B. Region selection

Modified activenet segmentation provides regions and from these regions the most probable regions for copy move detection is found by learning domain specific characteristics. Domain specific characteristics is found by splitting region to mesh and computing variance of mesh segments and calculating K partial sum of variances for region. These features of K larger partial sum of variances of regions are different for different images in various domains. A correlation is established between the K larger partial sum of variance as feature and whether to select the region as probable or not probable is established using fuzzy Gaussian membership function.

A collection of images in different domains is organized with their regions considered for copy move detection (known from ground truth). The feature of K larger partial sum of variance is extracted for each of the regions and this feature is associated with a class of 0(not probable region) and 1 (probable region) based on whether they are not considered or considered for copy move detection from ground truth. From this training set of feature and classes a fuzzy Gaussian membership function is built. Clustering is done on training dataset using Fuzzy C Means clustering with number of clusters as P=2. The cluster center is given as

$$D = \{ D_{e,q} , e = 1,2 \dots 5 \; and \; q = 1,2,3\} \quad (15)$$

Where D_(e,q) is the qth feature of the eth cluster.

The closeness of the qth feature of the rth data f r,q with qth feature of eth cluster is defined using Gaussian function as[26]

$$G\left(f_{r,q}, D_{e,q}, \sigma_{e,q}\right) = e^{\frac{(f_{r,q}-D_{e,q})^2}{\sigma_{e,p}{}^2}} \quad (16)$$

Where

$$\sigma_{e,q} = \frac{1}{N_e}\sum_{r=1}^{N_e}(f_{r,q} - D_{e,q})^2 \quad (17)$$

The closeness of features of rth data to the eth cluster is given as

$$\Psi_{r,e} = \prod_{q=1}^{P} G\left(f_{r,q}, D_{e,q}, \sigma_{e,q}\right) \quad (18)$$

Linear regression of input features is done to find the output label as

$$\Phi_{r,e} = W_{e,0} + \sum_{q=1}^{P} W_{e,q,f_{r,q}} \quad (19)$$

Features are multiplied with their regression coefficients (W) to find the cluster label.

$$\bar{N}(r) = \sum_{e=1}^{P} \Psi_{r,e} \Phi_{r,e} \quad (20)$$

The error of fitting is calculated between $\bar{N}(r)$ and $N(r)$ as given below

$$E = \sum_{r=1}^{N} ||\bar{N}(r) - N(r)||^2 \quad (21)$$

Two fuzzy Gaussian membership function are built one corresponding to probable region and another corresponding to not probable region. Non probable regions are filtered and copy move detection is done only over probable region.

C. Deep signature based copy move detection

Deep signature is computed for each of the probable regions identified in Section B. For each of the region, occlusion noises are added in different probabilities to generate multiple patches. On these patches QDCT coefficients are extracted. The coefficients with low frequency components (A_n^q) and high frequency components ($D_{s,1}^q$) are calculated for a image patch $f(x,y)$ using QDCT as

$$f(x,y) = A_n^q f(x,y) + \sum_{s=1}^{n} [D_{s,1}^q f(x,y) + D_{s,2}^q f(x,y) + D_{s,3}^q f(x,y)] \quad (22)$$

Applying QDCT, low frequency and high frequency components are obtained. Dimension reduction is done using two different strategies for high and low frequency components. Low frequency components in each band are dimension reduced using averaging. High frequency components in each band are dimension reduced using maximum value in each band.

To generate deep learning signature, a convolutional neural network (CNN) is used. CNN takes the reduced QDCT coefficients as input. This input passes through series of convolution, pooling and fully connected layer to get a reduced feature of dimension 1× 512. The configuration of CNN used for feature processing is given in Figure 2. Each image patch is passed to CNN to get reduced features. The reduced features of each patch are processed using a novel signature generation algorithm to generate aggregate signature.

The steps in the aggregation signature algorithm are given below

The output of CNN is vector of 1× 512 numbers. The number are converted to binary vector using Gaussian distribution function with mean zero and unit variance.

Binary vector corresponding to each image patch is subjected to inner product to provide a matrix D

On each element of the matrix, following transformation is done

$$tf(u) = \begin{cases} 1\ r.u \geq 0 \\ 0, r.u < 0 \end{cases}$$

$$\bar{u} = \{\mathrm{tf_{r1}(u), tf_{r2}(u), \ldots . tf_{rd}(u)}\}$$

The matrix is then converted to array in row major order and this array is called aggregation signature.

Since the aggregation signature is reduced dimension and binary, it is efficient to compare the aggregation signature using Hamming distance.

Aggregation signature is computed for each region. The regions are then matched for similarity using hamming distance. The regions whose hamming distance is less than threshold is detected as copy move regions. Figure 3 presents the overall process flow of the proposed solution. On the input image, segmentation is done using modified active net segmentation to get the regions. The most probable regions from it are found using the fuzzy Gaussian membership function. Deep signatures are extracted from the probable regions and hamming distance is calculated pair wise between the deep signatures of probable regions to detect the match.

4. Results

The proposed solution performance is measured against following CMH datasets.

Table 1. Dataset for experimentation

CMH-1	Dataset is characterized with 23 forged images manipulated using scaling operations
CMH-2	Dataset is characterized with 25 forged images manipulated using with rotation operations
CMH-3	Dataset is characterized with 26 forged images manipulated using resizing operations
CMH-4	Dataset is characterized with 34 images manipulated using successive rotation and resizing.

The copy more forgery detection methods proposed by Al-Moadhen et al [20], Ortega et al [22] are used for comparison. In addition, the deep learning signature method proposed in this work in compared in two modes of with and without optimization.

The effectiveness of fake detection is measured in terms of precision, recall, false positive ratio (FPR) and F1 score. Table 2 provides the comparison results for CMH-1 image dataset.

Table 2. Results for CMH-1 dataset

Solutions	Precision	Recall	FPR	F1 score
With optimization	98.11	98.23	1.96	98.55
Without optimization	98.21	98.77	1.98	98.63
Al-Moadhen et al	97.30	98.12	2.20	98.10
Ortega et al	97.87	97.59	2.1	98.33

The proposed optimization performed almost similar to that of deep signature without optimization for scaling based manipulations. But compared to Al-Moadhen et al and Ortega et al the proposed solution has atleast 1% higher precision.

Table 3 presents the results for CMH-2 dataset.

Table 3. Results for CHM-2 dataset

Solutions	Precision	Recall	FPR	F1 score
With optimization	97.21	97.17	1.37	96.55
Without optimization	97.21	97.27	2.13	96.64
Al-Moadhen et al	94.30	95.22	3.22	95.12
Ortega et al	95.17	94.62	3.01	95.47

For rotation manipulations, the proposed optimization performed almost same as that of without optimization in terms of precision, recall and F1 score. But FPR is less due to optimization as regions without shape characteristics are removed using modified active net segmentation. But these regions are used in Deep signature approach and textures were matched even though they were not copy move.

Table 4. Results for CMH-3 dataset

Solutions	Precision	Recall	FPR	F1 score
With optimization	96.21	94.11	1.37	95.55
Without optimization	96.21	93.77	2.32	94.71
Al-Moadhen et al	89.30	90.14	3.74	89.30
Ortega et al	90.17	89.62	3.50	89.62

For resizing manipulation proposed solution has very low FPR compared to all other works as even for smaller objects, the modified active net segmentation extracted the object accurately but in exiting approaches features of small object were cluttered with noises in the blocks in which the object is present.

The results for CMH-4 dataset are given in Table 5.

Table 5. Results for CMH-4 dataset

Solutions	Precision	Recall	FPR	F1 score
With optimization	94.21	93.17	1.42	95.63
Without optimization	93.21	92.77	2.42	94.63
Al-Moadhen et al	84.30	82.12	4.56	85.10
Ortega et al	85.17	82.64	4.25	86.42

For successive rotation and resizing manipulations, optimization approach achieved highest performance compared to all. Precision is at least 1% higher compared to existing works. The precision has increased due to two stage region selection of activenet segmentation and region filtering.

The computation time is measured across the solutions for 50 images and the average computation results are given Figure 4.

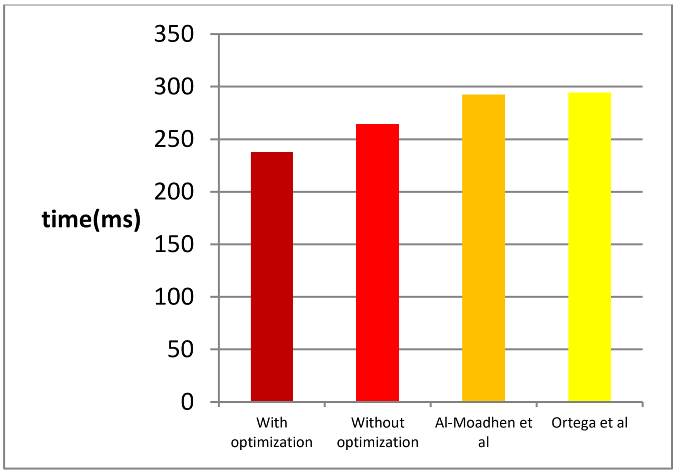

Fig. 4. Computation time comparison

The proposed optimization has reduced the computation time for copy move detection by atleast 11.23% compared to existing solutions. The computation time has reduced due to two stage region selection strategy used in proposed optimization. The effective regions to be matched for copy move have reduced in proposed optimization and this has contributed to lower computation time.

The proposed optimization performed almost similar to that of deep signature without optimization for scaling based manipulations. But compared to Al-Moadhen et al and Ortega et al the proposed solution has atleast 1% higher precision.

5. Conclusion

A region selection based optimization was proposed to reduce the computation time of deep signature based copy move forgery detection in this work. The two stages of region selection using modified active net segmentation and fuzzy Gaussian membership based region filtering has reduced the effective number of regions to be matched and this has reduced the computation time in proposed solution. The proposed region selection optimization did not compromise on the accuracy of copy move detection even though it reduced the area to be matched and it has also reduced the false positive rate. The proposed optimization has reduced the computation time by at least 11.23% compared to existing works.

References

[1] Mallonee, L.(2015) Infamously Altered Photos, Before and After Their Edits. Wired.

[2] Wikipedia contributors. (2019). List of Photo Manipulation Controversies. Wikipedia.

[3] Allbeson, T.; Allan, S. (2019). The War of Images in the Age of Trump. In Trump's Media War; Happer, C., Hoskins, A.,Merrin, W., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany

[4] H. Li, W. Luo, X. Qiu and J. Huang.(2017). Image Counterfeit Localization via Integrating Tampering Possibility Maps," in IEEE Transactions on Information Forensics and Security, vol. 12, no. 5, pp. 1240-1252

[5] Y. Li and J. Zhou. (2019). Fast and Effective Image Copy-Move Counterfeit Detection via Hierarchical Feature Point Matching. in IEEE Transactions on Information Forensics and Security, vol. 14, no. 5, pp. 1307-1322

[6] O. Mayer and M. C. Stamm.(2018). Accurate and Efficient Image Counterfeit Detection Using Lateral Chromatic Aberration. In IEEE Transactions on Information Forensics and Security, vol. 13, no. 7, pp. 1762-1777

[7] X. Bi and C.-M. Pun.(2017). Fast reflective offset-guided searching method for copy-move forgery detection. Inf. Sci., vols. 418–419, pp. 531–545

[8] X.-Y. Wang, S. Li, Y.-N. Liu, Y. Niu, H.-Y. Yang, and Z.-L Zhou.(2017).A new keypoint-based copy-move forgery detection for small smooth regions. Multimed. Tools Appl., vol. 76, no. 22, pp. 23353–23382

[9] S. Teerakanok and T. Uehara.(2018). Copy-move forgery detection using GLCM-based rotation-invariant feature: A preliminary research. In Proc. COMPSAC,pp. 365–369

[10] Chou, C.-L. and J.-C. Lee.(2018). Copy-Move Forgery Detection Based on Local Gabor Wavelets Patterns. In Proc. of Springer on International Conference on Security with Intelligent Computing and Big-data Services, vol. 733, pp 47-56

[11] B. Chen, M. Yu, Q. Su, H. J. Shim and Y. Shi.(2018). Fractional Quaternion Zernike Moments for Robust Color Image Copy-Move Counterfeit Detection. in IEEE Access, vol. 6, pp. 56637-56646

[12] M. Emam, Q. Han, Q. Li, and H. Zhang,(2017). A robust detection algorithm for image Copy-Move forgery in smooth regions. in Proc. ICCSS, London, U.K., Jul. 2017, pp. 119–123.

[13] Thajeel, Salam & Shakir, Ali & Rasheed, Waleed & Sulong, Ghazali. (2019). Detection Copy-Move Forgery in Image Via Quaternion Polar Harmonic Transforms. KSII Transactions on Internet and Information Systems. 13. 4005-4025. 10.3837/tiis.2019.08.010.

[14] Mahmood, T., et al. (2018). A robust technique for copy-move forgery detection and localization in digital images via stationary wavelet and discrete cosine transform. Journal of Visual Communication and Image Representation, vol. 53, pp. 202-214

[15] Hosny, K.M., H.M. Hamza, and N.A. Lashin, "Copy-move forgery detection of duplicated objects using accurate PCET moments and morphological operators," The Imaging Science Journal, vol. 66, no. 6, pp. 330-345

[16] Islam, M.M.; Karmakar, G.; Kamruzzaman, J.; Murshed, M. A .(2020).Robust Forgery Detection Method for Copy–Move and Splicing Attacks in Images. Electronics , 9, 1500.

[17] R. Cristin, J. P. Ananth and V. Cyril Raj.(2018).Illumination-based texture descriptor and fruitfly support vector neural network for image counterfeit detection in face images. in IET Image Processing, vol. 12, no. 8, pp. 1439-1449

[18] J. H. Bappy, C. Simons, L. Nataraj, B. S. Manjunath and A. K. Roy-Chowdhury.(2019). Hybrid LSTM and Encoder–Decoder Architecture for Detection of Image Forgeries. In IEEE Transactions on Image Processing, vol. 28, no. 7, pp. 3286-3300

[19] Liu, Y., Q. Guan, and X. Zhao.(2018). Copy-move forgery detection based on convolutional kernel network. Multimedia Tools and Applications, vol. 77, no. 14, pp. 18269-18293

[20] Al-Moadhen, Ahmed Abdulhadi Ahmed & Ridha, Mustafa & Khayeat, Ali.(2020). Splicing detection in color image based on deep learning of wavelet decomposed image. AIP Conference Proceedings. 2290. 10.1063/5.0027442.

[21] Huang, HY., Ciou, AJ. Copy-move forgery detection for image forensics using the superpixel segmentation and the Helmert transformation. J Image Video Proc. 2019, 68 (2019).

[22] Rodriguez-Ortega, Yohanna & Ballesteros, Dora & Renza, Diego. (2021). Copy-Move Forgery Detection (CMFD) Using Deep Learning for Image and Video Forensics. Journal of Imaging.7.59.10.3390/jimaging7030059.

[23] Patil, D. N. N. . (2021). Liver Tissue Based Disease Detection Using Pre-Processing and Feature Extraction Techniques. Research Journal of Computer

Systems and Engineering, 2(2), 17:21. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/27

[24] Mr. Kunal Verma, Mr. Dharmesh Dhabliya. (2015). Design of Hand Motion Assist Robot for Rehabilitation Physiotherapy. International Journal of New Practices in Management and Engineering, 4(04), 07 - 11. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/40

[25] Dhabliya, D. Security analysis of password schemes using virtual environment (2019) International Journal of Advanced Science and Technology, 28 (20), pp. 1334-1339.

Acknowledgements

I l would like to thank my guide Dr Ravikumar G K for his guidance and support throughout the work and I thank my HOD Dr T Logeswari T , who provided insight and expertise that greatly assisted the research.

Author contributions

Shashikala S: Conceptualization, Methodology, Software, Field study ,Result Analysis.

Dr Ravikumar G K: Visualization, Investigation, Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.