Characterization of splicing in digital images using gray scale co-occurrence matrices

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***Abstract*—Image forgery has become the main concern of the society over the past years due to an increase in the number of fraudulent image manipulations. Therefore, it has become a necessity to build an effective forgery detection method to check the integrity and authenticity of images. In this paper, an unsupervised method for classification of forged images and a supervised method for localization of forged regions is proposed. The methods use GLCM, a textural feature descriptor that uses pixel correlation in image to extract features from it. Further, for feature matching, Euclidean and Hellinger distance is used and finally, the localization of tampered region is performed. Euclidean and Hellinger distance is calculated separately on each image for comparison of the results. The experimental results showed that Hellinger outperformed Euclidean distance in feature matching and gave better localization results. In another approach, a bounding box is taken from the image to get the testing area and the training area. SVM classifier is used for classification of forged blocks and the authentic blocks in the image. The experimentation is performed on CASIA v1.0 dataset.**

Keywords—digital image forensics, forgery, image splicing, texture analysis, glcm

I. INTRODUCTION

With the advancement in image processing techniques, tampering with the digital images is becoming easier day by day and leaving no traces thereafter making difficult for humans to detect. This rapid growth leads to an increase in the number of image forgeries which can have a severe impact on any victim's life whose image has been manipulated and shared on social media. Therefore, it becomes necessary to investigate if image is original or not. Several different researches have been done by authors previously in this field of image forgery aiming to find the originality of images [1] [2]. Image forgery detection methods are mainly divided into two classes i.e. Active methods and Passive methods. In active method, it requires prior knowledge about watermark or signature inserted into image while capturing. These are used to check the originality of digital images. This embedded code is taken out from the given image and is checked against the original watermark, if it matches then image is real or authentic otherwise it is not whereas in passive method there is no prior information available about any such type of embedded code. In this technique, it is believed that there are some traces left in various forms of irregularities in image while tampering has been performed. These irregularities can be used to find the forgery in image. There are several techniques for tampering the digital images like retouching, copy-move, splicing, etc. [3] [4]. Retouching refers to change the looks in images like removing the dark circles beneath the eye, changing the skin colour and adding various filters to original photo in order to make it more attractive [5].

Now days, there are different types of application software available for image editing like Snapseed, TouchRetouch, Enlight and many more. This technique is mainly used in film and TV industry to hide all types of blemishes from person's faces making them more attractive. In copy-move forgery technique, small region or area is copied from the image and pasted into the same image at some other place. This technique is widely used by forgers to manipulate the original image and making false allegations on the other person to prove himself correct by giving false evidence. It is difficult to detect such type of manipulations as region is from same image so patterns like texture, colour, noise remain somewhat similar. Different methods have been proposed by authors in literature to detect copy-move forgery [6][7][8][9]. Splicing forgery method refers to copy pasting of a region on an image from different one or more images. Many researchers have proposed method for splicing detection like using textures as a feature for detection [10], using statistical methods [11], using inconsistencies in lighting as a feature [12] and many more. It is believed that there are some particular patterns which remain consistent for whole image. Therefore, if any image has been tampered, then its authenticity can be checked against those consistent patterns.

This paper aims to localize the tampered region of an image using GLCM for feature extraction and further using Euclidean and Hellinger distance for feature matching. Another technique has been proposed that consists a supervised approach for localisation which gives a precision of 79.9%. The rest of paper is organized in the following form. First, all the related work is discussed in Section II. Then Section III describes methodologies used for detection and localisation. Section IV presents all experimental details and results. Finally, the conclusion is discussed in Section V.

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II. RELATED WORK

Many different models have been proposed in the past for image splicing detection using different features like textural based features, statistical based features, transform domain features, space domain features and many more. In earlier research [13], an author proposed a statistical method, where histogram of approximate run length along the direction of edge gradient is used as a feature to detect image splicing detection. This method used 30-D feature vector for each image and gave 80.58% detection accuracy. In [14], DCT coefficient quantization based markov feature extraction model is used for image splicing detection with 98.5% accuracy for CASIA1 dataset. In this method, information loss is reduced by using DCT coefficient quantization. But on the same hand, additional feature reduction algorithms are also required to eliminate redundancy included by markov model-based features.

In [15], author used color shift inconsistency as a feature to find any manipulation in an image and then further used color temperature distance with threshold value using OSTU algorithm to localize the spliced region. Also, in previous research [16], textural feature Local Binary Pattern (LBP) is used along with spatial rich models (SRM) to detect passive image forgery. In addition to this, it also uses co-occurrence matrices and BEST-q-CLASS feature selection strategy. This approach is applied on IEEE IFS-TC image forensics dataset which contains 10 different forgeries including unaddressed forgeries such as histogram equalization, cropping etc. and produced 98.4% detection accuracy. In [17], multi-scale LBP is used with DCT coefficients on CASIA v1.0, CASIA v2.0 dataset for image splicing detection. On further using 10-fold cross validation for evaluation of SVM classifier with RBF kernel, performance metrics are computed and achieved 97.3% accuracy.

GLCM and HOG is used to extract texture based feature and edge features respectively [18] from color illuminant map. kNN classifier is then used to classify image as forgery if any face pair is indicated as inconsistently illuminated. However, this method is not able to detect all type of composite (spliced) images containing lighting effects. In [19], RBG and HSV color images are used. For each color channel red, green and blue of an image, feature vector is computed. Here color GLCM (CGLCM) and Gabor filters are used for textural feature extraction from an image. It was also found by authors that CGLCM based method gave better precision on small images in comparison to Gabor Filters (GF) method. Moreover, GF produced large size of feature vector as compared to CGLCM. In [10], textural feature GLCM (TF-GLCM) method is proposed to detect splicing forgery and further six different textural features are determined describing the properties of GLCM. TF-GLCM also gave promising results on post-processed images which are collected from CASIA v1.0 and CASIA v2.0 database. Detection accuracy achieved using this method is 98.54% on CASIA v1.0 and 97.73% on CASIA v2.0 with very less features. Furthermore in [20], scene classification is implemented by using graphical feature vector which is extracted using gray level-gradient co-occurrence matrix and then Gower's similarity coefficient model is used to perform similar matching and produced high precision. In addition to this, extension of GLCM to more than 1 scale is done using different methods like pyramid decomposition and Gaussian smoothing [21]. Multi-scale descriptor is further used to evaluate the performance on of the approach five texture dataset. Moreover, in [22] DTCWT is used to decompose the image into multiple directions giving broader information about the features and further GLCM is implemented. Then its statistical properties are calculated and then finally concatenation of the values followed by normalization is done to obtain final feature vector. This approach achieved high classification rate of 99.93% on VisTex test dataset and 98.82% on Brodatz dataset as compared to conventional methods such as DWT, Gabor.

III. METHODOLOGY

The main aim of image forgery is to remove useful information from the image by tampering the contents. The proposed method is inspired from paper [23] and aims to detect such manipulations in the image. The proposed methodology for the image forgery detection includes two approaches, one is supervised approach and other is unsupervised approach.

A. Unsupervised Approach

A brief flowchart of the unsupervised approach is illustrated in Fig. 1.

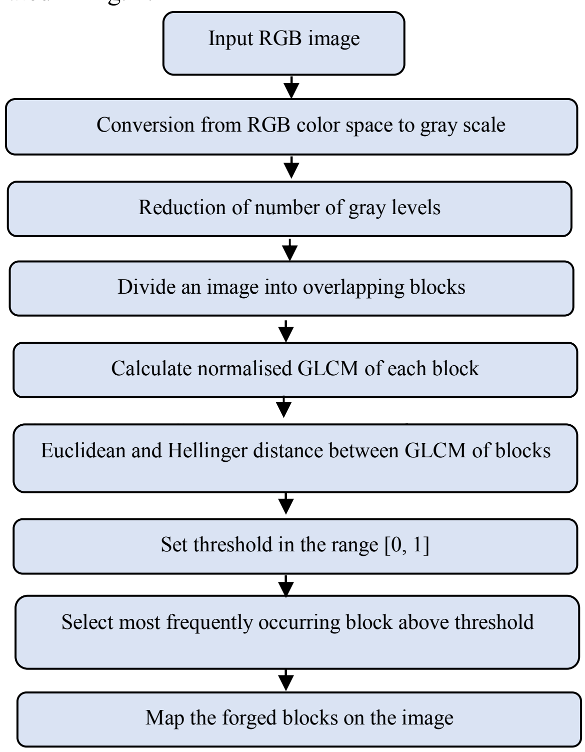

Fig. 1 Brief description of unsupervised approach

In the original image, each pixel is defined by the triplet intensity of Red, Blue and Green color. This triplet of RGB pixel is mapped into a single number result giving each pixel a gray-scale value.

- *Reducing the number of gray-levels*

The above method results in 256 gray levels with maximum value 255. With this maximum value, the computation becomes quite complex. So, in order to reduce the complexity, gray level values are reduced to 8. Thus, the new gray level values lie in the range of 0 to 7.

- *Dividing the image into sub image of overlapping blocks*

The 8 gray level image is further divided into 32×32 size of overlapping blocks and using a sliding window of step size 4. Blocks are traversed in order of left to right and when right end of the image is reached then traversal is from top to bottom and it goes on till the whole image is traversed. The step size of 4 means, next overlapping block selected is after four-pixel values in a horizontal or vertical direction depending on whether the traversal is from right to left or from top to bottom.

- *Calculating the normalized GLCM for each overlapping block*

A textural feature based on GLCM is extracted from each block. Corresponding to each block, GLCM is calculated. GLCM is a statistical measure of the spatial relationship between the neighbouring pixels of an image. It recognizes the textural characteristics of an image. It considers how many pixel pairs with certain intensity values are repeated over an image [24]. This textural information between the pixels of an image can be obtained at different values of distance (d) and angle (θ) between them. The following steps are used to calculate GLCM: First, matrix (A) for each block of dimension 32×32 containing pixel value is generated. Second, as matrix A contains values from 0 to 7 (8 gray level image) so second matrix B calculated is of size 8×8. Matrix B is calculated as follows:

B (i, j) is an element of matrix B where i and j denote row and column number respectively. B(i, j) value is calculated by counting the number of repeated pair value of (i, j) occurring in matrix A horizontally or vertically. This calculated matrix B is said to be Gray Level Co-occurrence matrix (GLCM). GLCM describes texture information related to the spatial distribution of gray levels in an image.

- *Calculating distance between GLCM of blocks:*

After GLCM is calculated, the next step is to find some dissimilarities between the textural features in the spliced and authentic images extracted using GLCM. This difference is used to mark the distinction between the two images. In the proposed study, one such method used is to calculate the Euclidean distance between the normalized GLCM of the blocks. After the Euclidean distance is calculated, it is normalized by dividing each value with maximum value obtained. Euclidean distance is computed between GLCM on basis of an element by element of the block. First, the difference between the elements of one block with the corresponding elements of the second block is calculated. Then each difference calculated is squared and finally summed together to get the final value whose square-root gives the Euclidean distance.

Other method used is to calculate Hellinger distance between the normalized GLCM and then even further normalizing the distance obtained. Mathematically, Hellinger distance is given by (1). Here, X = (x1,....,xk) and Y = (y1,….,yk) are two discrete probability distributions and the Hellinger distance H (X, Y) is a measure of similarity between these distributions.

$$\mathrm{H}\,(\mathrm{X},\mathrm{Y}) = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{k}\left(\sqrt{x_i}-\sqrt{y_i}\right)^2} \qquad (1)$$

- *Selecting the threshold value:*

After calculating the distance between GLCM, the next step is to find the blocks having maximum variation in the GLCM values. To find such blocks, only the blocks having greater value than a specific threshold are considered. With experimentation on different values between 0.0 and 1.0 it was found that 0.3 gives the best results.

- *Localise the forged area on image:*

The blocks obtained in the above steps are finally plotted over an image. The plotted area results in the identification of the forged area on the image.

B. Supervised Approach

In this supervised scenario, after the gray-scale conversion, the user is required to select a tentative training set and further, SVM classifier is used to learn the model parameters. All the steps involved in this method is described below in detail. Fig. 2, gives brief description of this approach.

- *Converting RGB image to gray-scale*

In the original image, each pixel is defined by the triplet intensity of Red, Blue and Green color. This triplet of RGB pixel is mapped into a single number result giving each pixel a gray-scale value. This results in 256 gray levels with maximum value 255. With this maximum value, the computation becomes quite complex. So to reduce the complexity, gray level values are reduced to 8. Thus, the new gray level values lie in the range of 0 to 7.

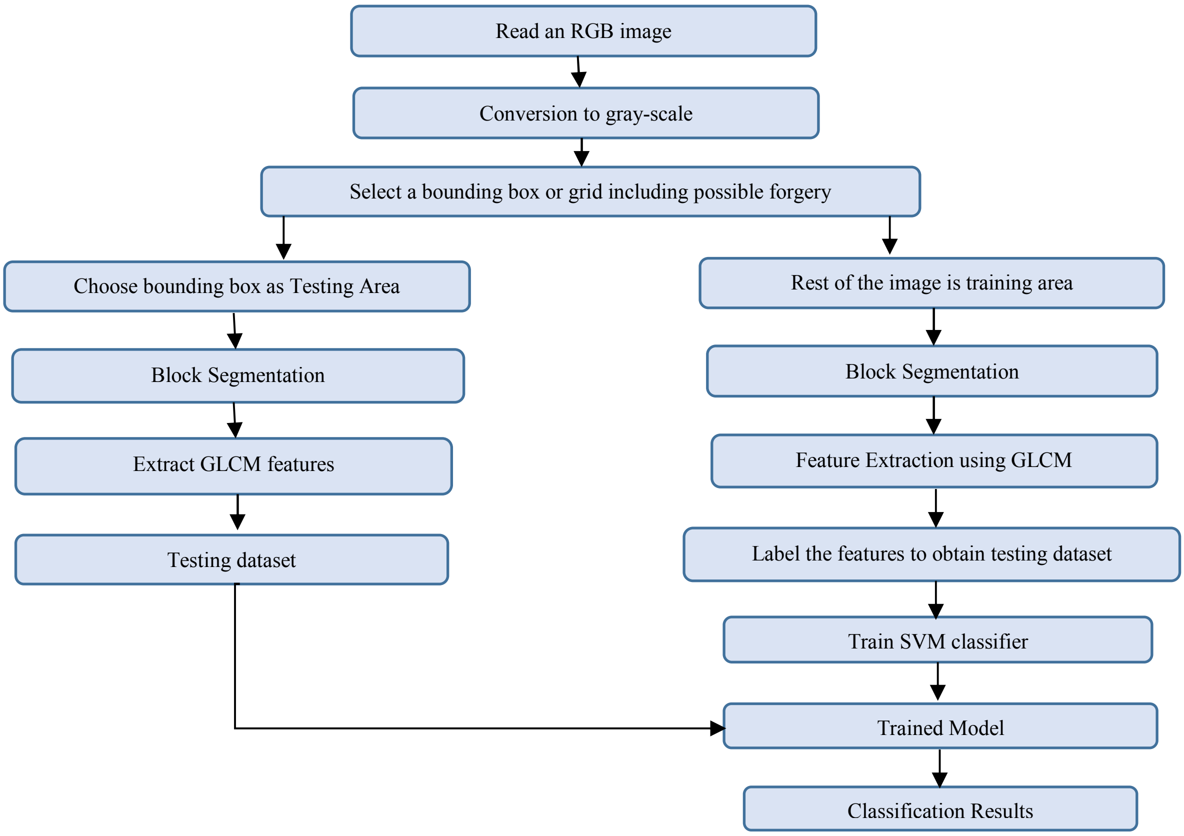

Fig. 2 Brief description of supervised approach using flowchart

- *Selection of bounding box:*

After the gray-scale conversion and reduction in gray-levels, the bounding box is selected randomly on the basis of the location of the spliced region on the image. By examining the original and the forged image, the approximate position of the spliced region is known and that spliced region is bounded by a box. Bounding box contains some part of the spliced region and some authentic region of the image. By varying the bounding boxes, more accurate forged region can be identified. If more than one spliced region is present then the regions are bounded accordingly. It should be noted that box only bound the discrete spliced regions.

- *Block Segmentation*

After the selection of the forged regions, the image is divided into small non-overlapping blocks of size 4×4 and sliding window of step size. Thus, total 6144 non overlapping blocks are obtained from the image. Blocks are traversed in order of left to right and when right end of the image is reached then traversal is from top to bottom and it goes on till the whole image is traversed. The step size of 4 means, next overlapping block selected is after four-pixel values in a horizontal or vertical direction depending on whether the traversal is from right to left or from top to bottom.

- *Labelling of features*

A textural feature based on GLCM is extracted from each block. Corresponding to each block, GLCM is calculated. It recognizes the textural characteristics of an image. It considers how many pixel pairs with certain intensity values are repeated over an image. The pixel values of each GLCM block acts as feature for the dataset. As size of each block is 4×4, so there are 16 features obtained corresponding to each block. The block is marked as forged if it contains forged area, else it is marked as authentic block. The blocks which lies on the forged regions are labelled as 1 while the blocks belonging to the authentic region of an image are labelled as 0. Thus, at the end the dataset comprises of 16 features with 6144 rows.

- *Training of SVM classifier*

After the features are labelled, dataset is divided into the training and testing dataset in the ratio of 80:20. The cases where the dataset was imbalanced, i.e. the labelled data as 0 for particular image are more than the labelled data as 1 for the same image or vice-versa For such images, upsampling or downsampling is performed in order to have a proper balanced data. After the division of the dataset, images are passed to SVM classifier. The SVM is used with linear kernel to train the model. The linear kernel is selected as it is used for data containing many features and for linearly separable data and moreover, linear kernel is faster. The labelled dataset is also linearly separable and contain 16 features. So, the training dataset is trained using SVM classifier with linear Kernel.

IV. Experimental Results

This section presents the performance analysis of the proposed method on images from publicly available datasets i.e. CASIA v1.0 and CASIA v2.0 dataset [22]. CASIA v1.0 contains 800 authentic images and 921 forged images of JPEG format. All the images (authentic and spliced) considered for experimentation is of fixed size 384×256 and no post-processing is performed on any image. In CASIA v1.0 dataset, among 921 forged images, there are 461 images on which copy-move forgery operation has been performed and rest of 460 images are composite (copy and paste operation from one image to other) images. CASIA v2.0 contains 7,491 authentic and 5123 forged images of varying sizes from 240 × 160 to 900 × 600 pixels and of different format i.e. JPEG, BMP, and TIFF.

A. Unsupervised Approach:

During experimentation for detecting the splicing forgery using unsupervised approach, RGB image of size 384×256 is taken as input which contains 256 gray levels. 256 gray levels of image are further converted to 8 gray levels. This image is further divided into overlapping blocks of dimension 32×32. Therefore, total blocks obtained by using a sliding window of step size 4 are 6144. GLCM is calculated for each overlapping block. As image is reduced to 8 gray levels, so GLCM calculated also consists of 8 levels only, i.e. dimension of GLCM is 8×8. For experimentation, normalized GLCM is calculated for d=1 and theta = 0 on the different forged images. Furthermore, Euclidean and Hellinger distance is calculated between the GLCM of blocks by setting different values of threshold between 0 and 1, and then again normalizing the distance obtained and finally analyzing the best threshold value for the proposed method. Experimentation is performed by taking different values of threshold such as 0.3, 0.5, 0.7 and 0.9. It was found that 0.3 as threshold value, gives best possible results for localization of spliced region.

In Fig. 3, experimental results are shown on one of the four images for both the Euclidean and Hellinger distance. First column shows the spliced image, second column shows the Euclidean results and third column shows the Hellinger results. Forged region is localised by red color rectangles over an image. In case of Euclidean distance, false positives (region which is not forged) are also detected to some extent whereas Hellinger distance detected forged region correctly.

B. Supervised Approach:

In supervised approach, the image is divided into non-overlapping blocks each of size 4×4. Here also, step size of sliding window taken is 4 and as a result, total number of non-overlapping blocks obtained for each image is 6144. Further, GLCM is calculated for textural feature extraction of each block. The pixel values of each GLCM block acts as feature for the dataset. Further featuring labelling is performed on the dataset. The blocks which lies on the forged regions are labelled as 1 while the blocks belonging to the authentic region of an image are labelled as 0. Then dataset is divided in ratio of 80:20 for training set and testing set respectively. SVM classifier with linear kernel is used to make the model learn. Further on the basis of this, model classifies the images of testing dataset as forged or authentic. Confusion matrix is obtained to evaluate the performance of the classifier. Table 1 describes the confusion matrix. It is observed that average accuracy of the SVM classifier is 82.28% and average precision achieved is 79.96%.

TABLE 1: Localisation results on images from CASIA v1.0 dataset using SVM classifier

	TP	**TN**	**FP**	**FN**	**TPR**	**TNR**	**Acc**	**Prec**	**F1**	**Miss Rate**	**Informedness**
Image 1	519	1029	122	173	0.75	0.89	83.9	80.9	0.78	25.0	0.6440
Image 2	641	875	129	136	0.83	0.87	85.1	83.2	0.83	17.5	0.6965
Image 3	598	870	172	211	0.74	0.83	79.3	77.7	0.76	26.1	0.5741
Image 4	354	921	100	205	0.63	0.90	80.7	77.9	0.70	36.7	0.5353
Average					**0.74**	**0.87**	**82.27**	**79.96**	**0.77**	**26.31**	**0.61**

C. Comparison of unsupervised and supervised approach

Table 2, describes the comparison between the two approaches used. Accuracy of supervised approach can be increased by changing the bounding box that is selected for testing region.

TABLE 2: Comparison of Supervised and Unsupervised approach for detection of splicing in digital images

	Unsupervised Approach	**Supervised Approach**
Accuracy (%)	82.93	82.28
Precision (%)	74.55	79.96
F1-score (%)	0.85	0.77

V. CONCLUSION

In this paper, method for localization of spliced region using pixel correlation is used. The proposed methodology is tested on CASIA v1.0 and CASIA v2.0 dataset. Two methods are used for the detection and localisation of spliced images, one is supervised method and other is unsupervised method. Overlapping blocks are considered in the unsupervised approach and non-overlapping blocks are used in supervised approach. Next, textural feature descriptor i.e. GLCM is used to extract the features from the images. Many different textural features can be extracted using GLCM, by changing the values of distance (d) and angle (θ) between the pixels. In unsupervised approach, Euclidean and Hellinger distances are calculated separately on the images to perform feature matching and finally localizing the tampered region and further results are compared and it is observed through experimental results that Hellinger distance performed better than Euclidean distance because in case of Hellinger, even small changes can be observed due to square-root of pixels in calculation of Hellinger distance. In supervised approach, featuring labelling is performed on the dataset. The blocks which lies on the forged regions are labelled as 1 while the blocks belonging to the authentic region of an image are labelled as 0. Then dataset is divided in ratio of 80:20 for training set and testing set respectively. SVM classifier with linear kernel is used to make the model learn and it is observed that SVM classifier achieved accuracy of 82.28% and precision of 79.96%.

In the future work, extension of GLCM to more than one scale using different methods like pyramid decomposition and Gaussian smoothing will be explored for image forgery detection. Moreover, hybrid classifiers will be explored to increase the accuracy of the proposed method. Also, the effect of other color components of image like chrominance and luminance will be explored for spliced forgery detection.

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Fig. 3 Experimental results of the proposed methodolgy.Red color rectangles indicates the forged region. First column is of spliced image, second column shows Euclidean results and third column shows Hellinger results over an image.