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Detection of Near-Duplicate Images using Statistical Texture Features

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***Abstract*—With advancements in digital image processing technology, it is tremendously effortless for anybody to re-acquisition high-quality multimedia from an imitating medium. Subsequently, digital image forensics has become progressively significant, in which photographic copying detection is one emerging field. The re-acquisition of digital media results in the introduction of artifacts. The visual quality dropping or blurriness is one of them, which can be effectively extracted using the texture features. State-of-the-art near-duplicate forensic methods are based on either some complex dictionary learning procedure or an improvisational group of features. In contrast to that, we proposed a model based on texture-based statistical features, namely, Multi-scale Local Binary Pattern (MLBP), the Log-Gabor Filter (LoG), and Dual-Tree Complex Wavelet Transform (DTCWT) for classification of near-duplicate or re-acquire images from the singly captured images. The adopted features are second-order statistical texture features. The extracted features perform well on the publicly available datasets, NTU-ROSE, ICL, and Mturk datasets. The comparisons with existing methods exhibit the computational accuracy and efficiency of the proposed model. Features extracted from the dataset of length 32 allows an SVM classifier to achieves an accuracy of 99% for the NTU-ROSE, 96% for ICL and 90% for the Mturk dataset.**

I. Introduction

Digital media nowadays plays a significant role in conveying information in all sectors, such as communication, biomedical imaging, cybersecurity, media, remote sensing, and defence. The whole world is moving towards digitization due to the accessibility of high-speed and economical digital devices and machines. Trillions of tools and machines generate a massive amount of data, merging the real and virtual worlds. Images and videos are the prime sources for carrying information in the digital era. The expressive ability of visual media with the simplicity of their acquisition, processing, distribution, manipulation, and storage is that they are more and more utilized to convey information over other sources of information carriers. Formerly and conventionally, there has been faith in the authenticity of visual media, such as photographs printed in newspapers or periodicals were considered the genuineness of the news. The video retrieved from a surveillance camera was considered the potential source of evidence in the court of law. Together, with certain benefits, the accessibility of digital visual media brings certain disadvantages. With the availability of inexpensive, high-resolution cameras coming in handy in mobile phones and low-cost and user-convenient editing tools such as Adobe Photoshop, CorelDRAW, and Meitu, which make editing images conventional; visual media forgery is ubiquitous. Any novice person can tamper with a photo or a video and upload it to the internet or any other digital media site, which leads to a severe threat to the integrity and authenticity of multi-media content security. To gain human trust, the digital image forensics domain becomes significantly essential.

One specific problem in digital image forensic is the classification between original or singly-captured images and near-duplicate images re-acquire from imitating screens. The two

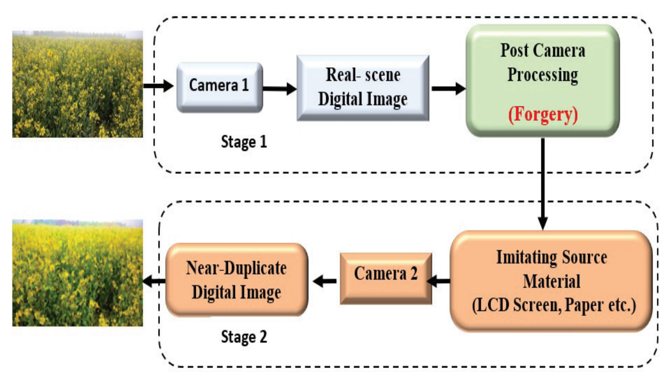

Fig. 1: Block Diagram Representation of Near-duplicate Image

sets of content generation procedures are explained in Figure 1. The real-scene digital image is captured using camera one and; is projected on an imitating medium. Camera two is used to re-acquire the digitally projected image, giving the output recaptured image. This whole process is termed a rebroadcast attack. According to [1], it is defined as a technical way an image/video is manipulated and then re-acquire to counter-attack against forensic techniques. Tampering artifacts used by current forensic methods are automatically decimated because the new recapture data is renewed. Essentially more than two cameras are used throughout this procedure, of the same or different specifications with an imitating medium. Undoubtedly, the motivation and authenticity behind the recaptured image raise suspicions. Data recapturing is often involved in the recreation of a fake photo and misleading the forensic system, as mentioned by other researchers [2], [3]. Some of the application areas of recaptured multi-media detection are anti-biometric spoofing detection, pirate video detection, and other fraudulent photographic copying problems.

In this paper, the statistical texture features are proposed to classify real-scene data and near-duplicate data. The experimental results conducted on the publicly available datasets outperform the state-of-the-art methods. The characteristics used in our research work contribute efficiently in detecting the micro-texture information for classification faithfully. The discrimination done based on these features is robust to a range of resolution and sharpness of the digital dataset, which is not efficiently done by typical statistical texture features such as GLCM, as discussed in Section V.

The remaining organization of the paper is as follows: Section II reviews the state-of-the-art for detecting near-duplicate images from LCD screens. In Section III, the technical specifics of the implemented methodology are presented, explaining the extracted texture statistical features adopted in our paper in detail. In Section IV, the detailed description of commonly available data sets of recaptured images for examining and estimating the framework is stated. In Section V, experimental results evaluated on the datasets are discussed and reported in-depth. In Section VI, we conclude the research paper and other future applications, followed by references.

II. Related Work

This section presents a brief review of the state-of-the-art work done in image recapture detection work. The detection of recapture digital visual media is a relatively new concept work in digital image forensics. In Section I, we have discussed the application areas of recapture detection. The survey on approaches given by researchers for image recapture detection is discussed briefly.

The methods comprise having a piece of preceding information about artifacts introduced in recaptured data when classified with the real-scene captured images. It is noteworthy that along with the computational distinction amongst both classes, according to the subjective evaluation testing detailed by Cao and Kot in [4] (2010) and by Mahdian et al. in [5] (2015), humans are not good observers at differentiating the near-duplicate images in a single simulant experimental environment. Some of the common attributes found in visual media re-acquired from an imitated medium are *blurriness*, *aliasing*, *noise*, *contrast, color*, and *texture non-uniformity*. Although the above fingerprints are often found in visual media, they can be eliminated by proper recapture settings [6] or are untrustworthy footprints for detection if used alone.

The researchers have used specific and unique attributes for detecting the various artifacts as mentioned above. J. Yin and Y. Fang [7] pioneered the methods to detect photographic copying from printed materials, such as photographs or magazines. They have used features to identify blurriness. According to the authors' Hang Yu, Ng T.T., and Sun Q. [8], the detection of recaptured images can be done by extracting the specularity distribution pattern left by printers on the paper. Gao X. et al. [9] have classified the recaptured image based on physical-based features such as blurriness, contrast, chromaticity, color histogram, specularity, and surface gradient. Dugelay and Kose in [10] proposed an algorithm based on characteristics of texture and contrast for recapture image detection.

In [4], Cao and Kot presented a low-level features based algorithm for texture patterns introduced by an LCD screen on re-acquire images. The aliasing, blurriness and color distortion artifacts are detected using multiscale local binary patterns, multiscale wavelet statistical and color moment parameters. Kai Wang [3], in his paper, has proposed simple technique-based correlation coefficients calculated on a pixel-wise basis in the spatial image subtractive domain for near-duplicate image detection. He focused on noise artifacts and included the image-statistical model of coefficients calculated from high-frequency in the spatial domain. T. Thongkamwitoon et al. [2] have presented the work based on blurriness and aliasing. The two parameters used, namely, an average line spread width and a sparse representation error for training dictionaries for the classification.

Some papers were available based on a neural networks approach for near-duplicate image detection from LCD screens [11][12]. Both the authors have given a CNN architecture for feature extraction and classification. Also, authors have concluded with pre-processing or using other neural networks besides CNN to increase classification accuracy. However, it still lacks in practical real-time situations such as pirated data detection or anti-face spoofing detection. This paper will focus on using image feature statistics to classify the photographic copying forensics problem. Using our proposed features, we can reach commensurable or improved results than the existing methods.

III. Proposed Method

In this segment, primitively, a quick introduction to the motivations in section III-A is stated and followed by an outline of the proposed texture features for detecting and classification of recaptured images is discussed in section III-B.

A. Motivation

In this section, we briefly explain the motivation behind detecting near-duplicate images. We have noticed two ongoing inclinations in the domain of recaptured data distinguishment based on the application areas. The first inclination is to identify near-duplicate images for fraudulent cases using various artifacts introduced by the image recapturing process and using sophisticated deep learning and machine learning tools to solve the grouping problem, as stated in Section II. The second trend is to detect near-duplicate video detection for video piracy.

It is worth noting that all the proposed methods desire to detect one or many specific alternations introduced due to the recapturing process. Spatial image-statistical techniques do not consider much usage of stronger pre-assumptions and are generic statistical features. Therefore, these methods are theoretically plain and computationally practical, without heterogeneous feature composition or complex learning procedures. Also, these methods are more efficient in gaining equitably good results on either original or post-processed geometric attacks images such as cropped images.

B. Texture Features

The classification model is formulated on the surface texture feature difference between the original and reacquire images. By observing the original and the corresponding near-duplicate digital images closely, we found some variations in texture. The resultant output of near-duplicate images is inevitable to acceptable loss of details. With the advancement in technology, the resolution of LCD screens improved to the most excellent quality, but it can hardly be matched with the high resolution capturing devices. Hence, more information is lost at the fine-scale level because of the frame rates and resolution mismatch. For example, it is observed that the mesostructure of the imitating medium modulates the recaptured image. Moreover, photographic screens of replay devices could reflect the surrounding illumination. A moiré pattern occurs on the photographic copied data because of the spatial frequency difference between a screen and a camera device.

To extract this texture information, we have used three operators, namely (1) Dual-Tree Complex Wavelet Transform (DTCWT), (2) Log-Gabor Filter, and (3) Multi-scale Local Binary Pattern (MLBP).

The block diagram representing the decomposition of a 2-D image using DTCWT into different sub-bands at different levels is shown in Figure 2. After calculating the DTCWT for six orientations, two statistical features- Variance and the Entropy of the resultant images is computed. The proposed operator is decomposed up to level 2. The total features dimension is of length 12 (6×2).

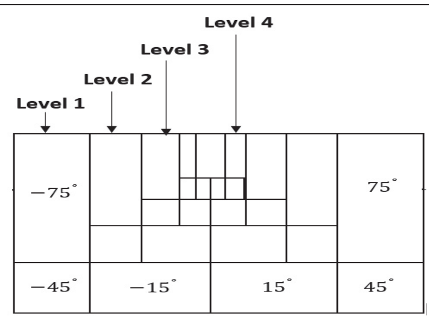

Fig. 2: DTCWT Sub-bands of 2-D Image

We had used another texture filter for extracting texture details. The Log-Gabor filter (LoG) is an improvement over the traditional original Gabor filter (GF). One of the limitations of the Gabor Filter is its bandwidth. The maximal bandwidth achieved by a GF is restricted to just overhead of one octet. That is not optimal if one is aiming for information over wide spectral and spatial confinement. For training and testing of the SVM classifier, we have considered two statistical features: the Variance and Entropy of the resultant images. The orientation considered here is six with a scale of one. The total features dimension is of length 12 (6×2). The features extracted by the MLBP operator is shown by Eq. 1 as follow:

$$\mathbb{LBP}_{P,R} = \sum_{p=0}^{P-1} A(G_p - G_c)2^p \tag{1}$$

Where the greyscale centre pixel value is represented by the symbol G_c for (x_c, y_c) coordinate and P refers to a number of pixel points spread equally on a radius of R from the centre. The function A is a binary function given by Eq. 2:

$$A(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases} \tag{2}$$

To generate efficient results, Multiscale LBP is used here with P, R values (8,1), (16,2), (16,3), and (24,4) for the whole image. Finally, the mean and variance of the selected orientation are calculated. The total feature dimension of MLBP is 8.

In this paper, for a given set of input images, the feature vector of length L is computed, consisting of statistical texture features in the spatial image domain. The value of L is mentioned previously for all the texture operators. The block diagram of the training and testing stages of the stated research framework is shown in Figure 3. During the training phase, the texture, as mentioned earlier, texture-statistical features are computed separately from original images and near-duplicate image sets. The extracted feature vectors for both groups' images, along with the corresponding class names (e.g., "1" for the original photos and "-1" for the near-duplicate photos), are given into the Support Vector Machine (SVM) classifier for training a grouping model. During the testing phase, for a given input image, feature vectors are calculated from it and inputted into the classifier model to get the output result of whether the given input image was a real-scene or near-duplicate one. It is worth stating that the proposed method is computationally very efficient because of spatial features only. The forensic system framework is summarized in Algorithm 1. The proposed algorithm is straightforward and based on supervised machine learning. The extracted features are used to train the model and the classification model can be used for detection of near-duplicate images.

The texture analysis aims to find a distinct way of characterizing the underlying features of textures and representing them in some more straightforward but unique form. The characteristics used should be robust and should provide accurate classification and segmentation accuracy. The commonly used statistical texture features are Gray Level Co-occurrence Matrix (GLCM), associated with extracting the second-order texture statistics features from an image. Several texture features are extracted from the GLCM. Features such as contrast, correlation, energy, entropy, homogeneity, and variance are general. But the classification of near-duplicate detection based

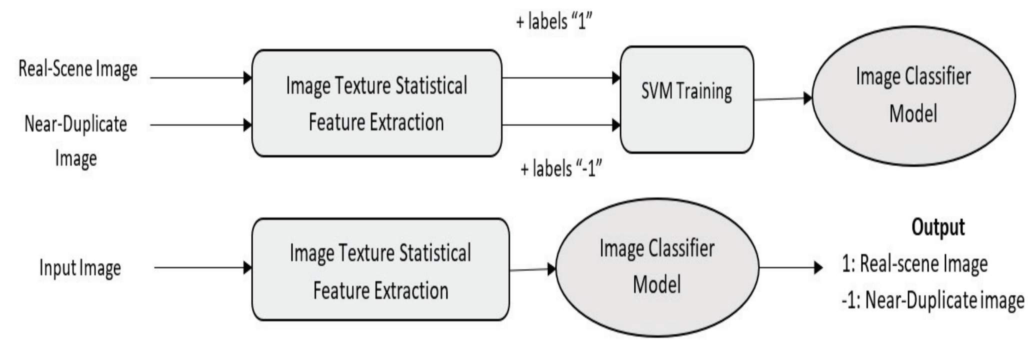

Fig. 3: Block Diagram of both training and testing phase of the proposed near-duplicate image classification model

Algorithm 1: Statistical-Texture Features Extraction

Input: I set of real-scene and near-duplicate input images, N is number of neighbours element, R is the radius about center element, $nScale$ is the number of wavelet scale. $nOrient$ is the number of filter orientation, $minWL$ is the minimum wavelength of smallest scale filter

Ouput: $lbp_{8,1}, lbp_{16,2}, lbp_{16,3}, lbp_{24,4}$ are the multi-scale LBP paramteres, V is the variance, E is the entropy parameter.

```
foreach Input Image I do
    compute imcrop(I);
    compute DTCWTFunction(I, nScale, FilterBank);
    compute V, E value;
foreach Input Image I do
    compute imcrop(I);
    compute LogGaborConvolve(I, nScale, nOrient, minWL);
    compute V, E value;
foreach Input Image I do
    compute imcrop(I);
    compute rgb2gray(I);
    foreach (N,R) do
        compute extractLBPfeatures(I,N,R);
```

on such direct statistic features is not sufficient. This can be shown from the results evaluated in section V.

IV. Experimental Datasets

In this section, the brief detailing of the two foremost publicly available versatile databases for near-duplicate detection used by researchers for result evaluations is described. To the best of our understanding, publicly, these are the two enlarge versatile datasets of recaptured images of high-resolution. The near-duplicate attack can be classified broadly into four types: (1) *Photographing a printed image*, (2) *Scanning an image*, (3) *Capturing a projected or displayed media through digital display*, and (4) *Capturing a screen-grab of a display media.*

1. ***NTU-ROSE Database*** [4]
   Cao and Kot formed the dataset in 2010 at the Nanyang Technological University (NTU), Singapore, in the ROSE laboratory. It comprises a total of 2776 near-duplicate images and, the original single captured images include 2710 in total. Out of 2710 copies, 2001 images were captured using five digital cameras of different brands. The remaining 709 datasets of images comprise single captured images of high-resolution downloaded from cyberspace, such as the Flickr website, and others have tampered images. They have used three different cameras of high resolution and three different LCD screens for imitating the original pictures for recapturing. Thus, contributing a total of nine combinations of display cameras. To ensure the high-quality of recaptured images, the environment settings were manually and heuristically adjusted. The dataset can be accessed from the URL http://rose1.ntu.edu.sg/datasets/recapturedImages.asp after signing the release agreement. Some examples from the NTU-ROSE dataset are shown in Figure 4.
2. ***ICL Database*** [2]
   The dataset was formed by Thongkomwitoon et al. team at the Imperial College London (ICL). The dataset consists of 1035 original images and 2520 near-duplicate images, but online-only a portion of it is openly accessible, comprising a total of 900 authentic images and 1440 near-duplicate images. For the original image, nine cameras were used of varying resolution from 5MP to 20 MP. Recapturing was done from eight different cameras. The recapturing procedure was done using the IPS LCD screen with a resolution of 1920×1080 pixels with LED backlighting. The environmental and experimental parameters were controlled and theoretically calculated for getting high definition and high-quality near-duplicate images with the least amount of aliasing effects. The dataset can be accessed from the URL http://www.commsp.ee.ic.ac.uk/

Fig. 4: In the top row are the four singly captured images from the NTU-ROSE database [4]. The corresponding recaptured images are shown in bottom row.

~pld/research/Rewind/Recapture/. Some examples from the ICL dataset are shown in Figure 5.

3. ***Mturk Database*** [13]
It is the latest dataset formed by the Shruti Agarwal et al. team in 2018. The dataset consists of 10,000 original images and more than 20,000 near-duplicate images, captured using different imitating media like LCD screens, scan printout, printer output and screengrab photographs. We have used only the LCD recaptured images. The original images of 1,956 and near-duplicate images of 1,956 were used. Recapturing was done from 119 different cameras. The recapturing procedure was done using the 129 LCD screens with varying resolutions. The dataset can be accessed from the URL https://agarwalshruti15.github.io/. Some examples from the Mturk dataset are shown in Figure 6.

From the example, it can be clearly shown that an unaided human eye can difficultly classify the near-duplicate from the singly captured original ones if presented simultaneously to them with no prior information. We can perceive that the three databases comprise a considerable amount of high-quality, versatile real-scene and near-duplicate images with diversified digital camera models and various imitating screens. The main variance between NTU-ROSE, ICL and Mturk databases belongs to the recapturing process, resulting in a relatively distinct level of aliasing and tampering artifacts in the resultant images. Down the line, we examine our proposed feature algorithm on all datasets and organize a comparative study with the current two state-of-the-art frameworks. The validation of results is mentioned in elaboration in Section V.

V. Experimental Results and Discussion

Our research aims to distinguish between two categories; the first set is the real-scene or original image from the second set of re-acquire or near-duplicate images. The problem is a grouping or classification category. After extracting statistical texture feature vectors, we train a supervised machine learning classifier model known as Support Vector Machine (SVM) with a non-linear Radial Basis Function (RBF) kernel in MATLAB 2015a software. We randomly divide the dataset into a 60:40 ratio for training and testing, respectively. To estimate the accuracy of our presented research problem, we compare the results of two near-duplicate image classification methods. The first method is proposed by Thongkamaitoon et al. (2015) [2], and Kai Wang presents the second (2017) [3]. Also, we have tested our proposed model on all three data sets. The statistical texture features are better than the general statistical features is also tested by evaluating the GLCM texture features for all datasets.

A. Evaluation on three Datasets

In this segment, we present and discuss the experimental results evaluated on NTU-ROSE, ICL and Mturk Database. The NTU-ROSE recaptured database is enormous in comparison with other available datasets. The dataset images are of high quality and excellent visual appeal. We can observe slight aliasing-like artifacts when carefully inspected. The aliasing artifacts in this dataset are much stronger than another two tested datasets, making this dataset much less challenging for near-duplicate image detection. In contrast with ICL and Mturk datasets, the NTU-ROSE dataset also consists of tampered images, making the evaluation interesting. The tampering includes content alteration, color alteration, blurriness, and weak to strong aliasing effects. We have conducted the

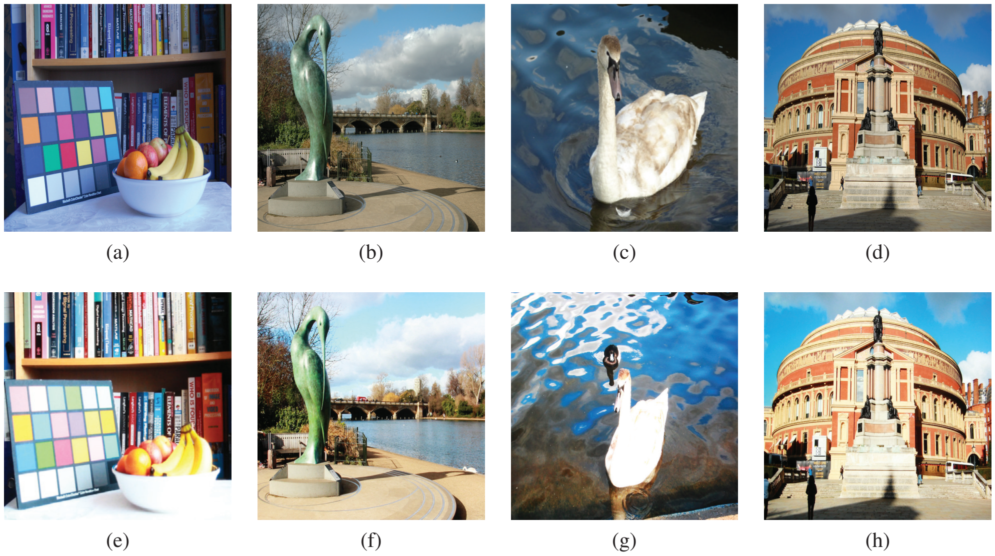

Fig. 5: In the top row are four real-scene images from the ICL database [2]. The corresponding recaptured images are exhibit in the bottom row showing the plausible and convincing visual similarity between both sets of images.

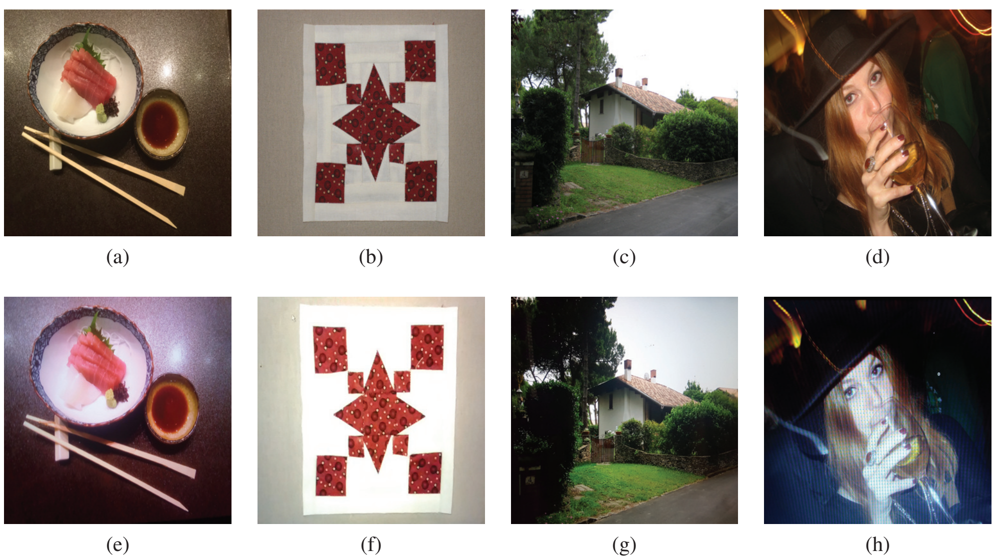

Fig. 6: In the top row are four real-scene images from the Mturk database [13]. The corresponding recaptured images are exhibit in the bottom row showing the plausible and convincing visual similarity between both sets of images.

results of MLBP on grey-scale images and of LoG filter and DTCWT on colored images fixed with width to height of 1024 $\times$1024 pixels. This dimension is maintained for fast computation. The 5-fold cross-validation parameter on training set data was used in determining the SVM hyperparameters. The ICL database is a more challenging dataset, and the dataset comprises high-quality images with aliasing artifacts invisible to unaided human eyes. All the pictures are cropped to 1024$\times$1024 dimensions from centre for experimentation. Table I presents the results of all three datasets.

TABLE I: Resultant classification accuracies of the hand-crafted features on respective Datasets

Image Size	**Dataset Name**	**Features Accuracy (%)**			
		GLCM	**MLBP**	**LogG Filter**	**DTCWT**
1024$\times$1024	NTU-ROSE	72.14	99.82	89.29	75.00
1024 $\times$ 1024	ICL	66.43	98.57	88.57	69.71
1024 $\times$ 1024	Mturk	61.60	87.40	84.44	66.29

Overall, our texture features give outstanding discrimination accuracy. The accuracy percentage of DTCWT is slightly low in comparison with the other two features. The accuracies of ICL and Mturk datasets are a bit less than the NTU-ROSE results. It may be due to the fact the texture features discriminate based on aliasing and blurring artifacts. At the same time, near-duplicate images in the ICL and Mturk databases have an inconsiderable amount of so-called distortions. Thus, the proposed specific texture features might become less distinct and result in lower classification accuracies. Also, the amount of devices used in creating Mturk dataset make it more diverse and versatile. This shows the fragility of homogeneous datasets.

We have also computed the GLCM statistical texture features on all datasets, showing the ineffectiveness in classification accuracy compared to the other texture-statistical features proposed. The resultant accuracy is shown in Table I. The list of features extracted is *contrast* (C), *auto-correlation* (AC), *energy* (E_1), *entropy* (E_2), *homogeneity* (H), *variance* (V), *a sum of average* (S_A), *a sum of variance* (S_V), *a sum of entropy* (S_E), *the difference of variance* (D_V), *a difference of entropy* (D_E), and *information measure of correlation* (I). The feature length is 12, which is more than the proposed featured dimension of other features. The highest accuracy achieved by simple statistical texture features is 72.14% only for the NTU-ROSE dataset, as shown from the results, which is very low compared to the accuracy achieved by more sophisticated statistical texture features such as MLBP and other frequency-based texture features. The handcrafted statistical texture features significantly outperform the other statistical features like GLCM.

B. *Comparative Experimental Results*

This subsection evaluates a relative comparison amongst the three different datasets with the two state-of-the-art methods. We have computed comparative results with the technique given by T. Thongkamwitoon et al. (2015) [2] and the method provided by Kai Wang (2017)[3]. Table II shows the comparative accuracy results. The accuracy values of the method proposed in [2] for the ICL database were extracted from their paper. From the results, we can conclude that our method's proposed features give more efficient classification accuracy for the NTU-ROSE and Mturk database compared to the other two proposed techniques. On the other hand, the accuracy provided by our proposed features for the ICL database is approximately less by 1% in comparison with the other two techniques. The variation in accuracies is negligible for the NTU and ICL datasets. It may be due to the excellent functioning of MLBP in summarizing the differentiability properties of texture between the two classes. The accuracy achieved by the Mturk dataset for all the methods is relatively more minor. It may be due to the versatility of the medium and re-acquiring devices used for creating the dataset.

In addition to the classification accuracy results, we have summarized the concerning computational efficiency. In practical forensic applications, a system needs to be fast. The execution time for the feature extraction and classification of our presented methodology in contrast with the Thongkamwitoon et al. [2] and Kai Wang [3] methods are shown in Table III. The values presented in this table are for the average results evaluated on collective images of a set of 200, including an equally divided portion of singly captured images and near-duplicate images of dimensions 1024×1024 from the ICL database. The simulations were carried out with MATLAB 2015a software on Windows 8 platform using GPU with configuration Intel® Xeon(R) CPU specification E5-2620 v2@ 2.10Ghz× 12.

TABLE II: Classification accuracies of the methods [2] and [3] and our proposed method on all the datasets

Method	ICL Database	NTU-ROSE Database	Mturk Database
Thongkamwitoon et al. [2]	97.44%	99.03%	79.54%
Kai Wang[3]	97.71%	99.18%	87.90%
Proposed Method	**96.25%**	**99.91%**	**89.97%**

TABLE III: Comparative values of the average execution time per image (in seconds) for our proposed method with methods in [3] and [2]

Method	Thongkamwitoon et al. [2]	Kai Wang [3]	Proposed Method
Feature Extraction	38.9762	30.2002	MLBP : 1.6729 DTCWT : 1.0849 LoG : 2.8059
Classification	7.7842	0.0074	MLBP : 0.0017 DTCWT : 0.0015 LoG : 0.0011

We can note from Table III that our proposed method is significantly faster, with the total features extraction time per image of about 5.5637 seconds versus about 30.2002 seconds for the method proposed in [3] and 38.9762 seconds for the proposed method [2]. Also, the classification time for our proposed method is less than the other two state-of-the-art methods due to the less disability of feature vectors. Different from the state-of-the-art work which uses complex machine learning tools, the proposed method is very conceptually simple and computationally effective.

VI. Conclusion and Future Work

In this present study, we presented a texture-statistical-based scheme to detect near-duplicate images. Our method is straightforward, simple, and effectively computational. More accurately, we focused on global texture statistics of mixed moments in the spatial domain. The extraction process is highly robust and real quick. The feature extraction time per image is 5.5 seconds and classification takes negligible time. The respective digital image forensic system can advantageously manage the objective of differentiating between the two real-scene and near-duplicate images on diversified databases comprising very high to moderate resolution images captured using the LCD screens as imitating sources. Our method accomplishes a higher accuracy percentage when compared with the most recent methods while enduring an extremely robust, quick, and consistent model.

Concerning future work, we would like to work in a direction related to practical applications. It would be interesting to combine our technique with an anti-biometric spoofing system and anti-pirate video copy detection. Also, the proposed features can be used to detect rebroadcast attacks through other imitating media sources such as printed photographs, screen-grab images, etc. At last, we intend to study other domain modification techniques to encourage the practical implementation of image near-duplicate forensic systems.

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