

Effect of Image Splicing and Copy Move Forgery on Haralick Features of a Digital Image

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Abstract

Nowadays, digital images have become the fastest way of transferring information, but the existence of advanced photo-editing tools makes it easy to alter digital image content which may be used as proof in a legal case, thus creating a serious problem. The most frequent techniques of image forgery include splicing and copy move. Splicing is an image forgery technique in which, the forger crops a part of the first image and places it in the second image while Copy move forgery is a type of image manipulation that involves copying and pasting at least one component of an image onto other areas of the same image for the purpose of duplication or removal of objects in the image. Finding the integrity of a digital image is critical since it can be used as a legal proof in a multitude of sectors, including investigation of a crime scene. Equally, finding the features of an image that change as a result of image manipulation such as copy move and splicing is very important as this can be used to distinguish between forged and original image. Therefore, in this paper, we looked upon the effect of image splicing and copy move forgery on haralick features of a digital image. CoMoFoD dataset and Images frames extracted from original and spliced videos were used in this experiment. The result of this experiment shows that splicing and copy move manipulations have no effect on haralick features of a digital image. As a result, these features cannot be used to tell if an image has been spliced or was manipulated by a copy move forgery.

Keywords: *splicing, copy move, forgery, haralick features*

1. Introduction

The availability of powerful and easy-to-use photo-editing techniques and software like Adobe PhotoShop, as well as smart phone apps like Snapseed, has made it simple to change the content of an image that could be used as evidence during a legal investigation without leaving any visible evidence of the change. The creation of a digital image forgery usually involves combining objects or people from different images into a single composite. There are various types of forgeries that can be done on a digital image. The most prevalent forgeries are splicing and copy-move (cloning), which modify images in such a way that they are barely perceptible by the human perceptual system. (RAO, NI, & ZHAO, 2020).

Changing the content of a digital image can change the image's underlying statistics. This paper focused on identifying the effect of image splicing and copy move manipulations on haralick features of a digital image. Haralick features are digital image features that are computed based on the gray level co-occurrence matrix (GLCM). As a function of the gray level, GLCM indicates how many times each gray level appears in a pixel with a specified geometric position compared to adjacent pixels. The following are some of the features that can be obtained from GLCM: Energy, Correlation, Contrast, Homogeneity and Dissimilarity. It is crucial to figure out how image splicing and copy move forgeries affect these characteristics because knowing the effect of these manipulations on haralick features may help in the detection of forgery in a digital image, since the creation of an image forgery often involves merging objects or people from separate images into a single image. The process of image splicing is depicted in Figure 1.

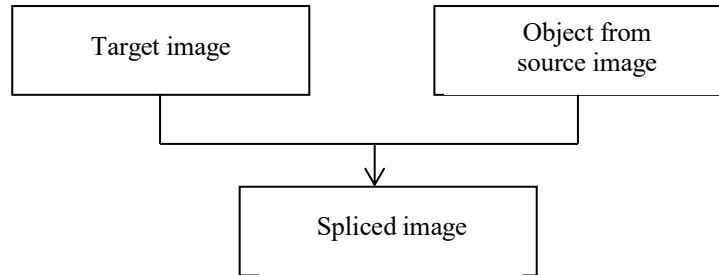


Figure 1. Image splicing process

The rest of this article is arranged in the following manner. The literature on splicing forgery, copy move forgery, and techniques for detecting splicing and copy move forgeries in digital images or videos is reviewed in the related work section. The feature extraction and description of the dataset utilized in this experiment are described in the Methodology section. The experiment's results and discussion are presented in the Results and Discussion section. Finally, the Conclusion section brings the paper to a closure and suggests prospective directions for further research.

2. Related Works

Image splicing is a common type of image forgery where a region from one image is copied and pasted into another image thereby creating a composite image called spliced image (Park, Han, Moon, & Eom, 2016). For example, an object could be cloned from one image and placed onto another to conceal or fake the existence of an incriminating object. The source image and target image in splicing forgeries could either be distinct from each other (inter-frame splicing) or the same (intra-frame splicing) (Singh & Aggarwal, 2017). Figure 2 depicts an example of image splicing, in which the shark and helicopter images are combined into one image.



(a)

(b)

(c)

Figure 2.(a) Helicopter; (b) Shark; (c) composite image (Kashyap, Parmar, Agarwal, & Gupta, 2017)

Copy move forgery is a prevalent and simple image manipulation technique in which at least one component of an image is copied, moved, and pasted into other areas of the same image in order to duplicate or remove items from the image (Muzaffer & Ulutas, 2019). In Figure 3, a pigeon is copied and pasted onto the same image as an example of copy move forgeries.



(a) Authentic image (b) Copy move forgery image

Figure 3: Example of copy move forgery (Tralic D., Zupancic I., Grgic S., & M., 2013).

In the literature, several techniques for image/video splicing and copy move detection have been proposed. However, experiments have shown that none of these techniques uses haralick features in the detection process. For example, (Kaizhen & Zhang, 2012) uses features taken from image quality metrics (IQMs) and moments of characteristic functions of wavelet subbands to detect splicing forgeries. (Manu & Mehtre, 2015) uses visual artifacts in uncompressed images to detect image splicing. Furthermore, to detect image splicing, (Park et al., 2016) used characteristic function moments for the inter-scale co-occurrence matrix in the wavelet domain. To detect and pinpoint the existence of splicing in an image, (Cozzolino & Verdoliva, 2016) used a recurrent autoencoder. For efficient detection and localisation of image splicing and copy-move forgeries, (Chen, McCloskey, & Yu, 2017) used camera response functions (CRF).

For the identification and localisation of splicing image forgeries, (Griebenow, 2017) used residual Convolutional Neural Networks (CNN) paired with an autoencoder. (Sulaiman et al., 2019) uses a convolutional autoencoder and the Generic Object Tracking Using Regression Network (GOTURN) algorithm to detect and localize video splicing forgeries. (Muzaffer & Ulutas, 2019) presented a deep learning-based framework for copy move forgery detection and localization. The feature vectors of image overlapped sub-blocks were extracted using a pre-trained AlexNet convolutional neural network. (RAO et al., 2020) detects image splicing using a deep CNN-learned local feature descriptor. (RHEE, 2020) proposed utilizing texture analysis of the median filter residual of the forged image to classify the Cut-paste region in a spliced image. (Thakur & Jindal, 2020) proposed a hybrid deep learning (DL) and machine learning-based approach to detect copy move and splicing forgery. The forgery is detected using deep learning technique and the localization of the forgery is done using Machine Learning based colour illumination algorithm. (Niu, Tondi, Zhao, Ni, & Barni, 2021) proposed an end-to-end system for detecting and localizing image splicing activities, which included the ability to differentiate spliced regions from distinct donor images.

3. Methodology

In this section, we'll go through how to extract image features using a gray level co-occurrence matrix, as well as the image dataset we utilized for the experiment.

3.1 Feature extraction

Feature extraction is a technique for obtaining features that can be used in image processing tasks such as selection and classification. Shape, texture, color, and other characteristics are used to characterize the image's content (Choras, 2007). Haralick features are digital image features that are computed using the GLCM. As a function of the gray level, GLCM indicates how many times each gray level appears in a pixel with a specified geometric position.

The co-occurrence matrix $p(i,j)$ counts how often pixels with gray values i and j appear together at some d in a given direction. The direction can be set to one of four values: 0, 45, 90, or 135 degrees, while the distance is determined by the texture resolution (Rad, Tab, & Mollazade, 2012). To reduce feature space dimensionality, Haralick features such as Energy, Correlation, Contrast, Homogeneity, and Dissimilarity can be obtained from the co-occurrence matrix (Choras, 2007).

The number of repeated pairs is measured by energy, the gray level variations between the reference pixel and its neighbor are measured by contrast, the linear dependence of the pixel intensity on its position in the image is measured by correlation, and homogeneity is measured by how intimate the distribution of elements in the GLCM is to the GLCM diagonal. These haralick features are computed using 1–5 for $(m \times n)$ co-occurrence matrix (Campbell, Kang, & Shokouhl, 2017).

$$\text{Energy} = \sum_{i=1}^m \sum_{j=1}^n p(i,j)^2 \quad (1)$$

$$\text{Contrast} = \sum_{i=1}^m \sum_{j=1}^n (i - j)^2 p(i,j) \quad (2)$$

$$\text{Correlation} = \frac{\sum_{i=1}^m \sum_{j=1}^n p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (3)$$

$$\text{Homogeneity} = \sum_{i=1}^m \sum_{j=1}^n \frac{p(i,j)}{1 + |i - j|} \quad (4)$$

$$\text{Dissimilarity} = \sum_{i=1}^m \sum_{j=1}^n |i - j| * p(i,j) \quad (5)$$

Where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of probability matrix p_x and p_y .

3.2. Dataset

The dataset used for the experiment comprises of image splicing datasets and copy move forgery (CoMoFoD) datasets. The image splicing dataset includes 3,560 original and spliced images from the GRIP video dataset, which may be downloaded at <http://www.grip.unina.it/download/prog/ForgedVideosDataset/Splicing/>. This dataset contains ten short videos that have been spliced together using Chroma-key composition. Table 1 list the videos

Table 1.Characteristics of video datasets

S/N	Video	Total Number of frames	Number of forged frames
1	Tank	335	191
2	Man	399	207
3	Cat	281	136
4	Helicopter	488	292
5	Hen	373	169
6	Lion	294	228
7	Ufo	306	96
8	Tree	302	240
9	Girl	371	162
10	Dog	310	186

All of the frames are the same size, measuring 720 x 1280 pixels. Figures 4 and 5 depict frame examples derived from authentic and forged videos, respectively.



Figure 4: Original frames from three non forged videos



Figure 5: Forged frames from three forged videos (Splicing forgery)

CoMoFoD refers to Copy Move Forgery Detection Image Database (Tralic D. et al., 2013). The data can be found at <http://www.vcl.fer.hr/>. The dataset contains 5,200 original images as well as 5,200 images that have been tampered with using copy move forgeries. Sample images from the CoMoFoD dataset are shown in Figures 6 and 7.



Figure 6. Original images(Tralic D. et al., 2013)



Figure 7. Images affected by copy move forgery (Tralic D. et al., 2013)

4. Results and Discussion

In this paper, the GLCM was calculated using distances=[1,2,3] and the angles=[0,45,90 and 135]. Five haralick features (energy, contrast, correlation, homogeneity and dissimilarity) were calculated for each image. Table 2 and 3 show the energy, contrast, correlation, homogeneity and dissimilarity values calculated from first 10 frames from Man original and spliced video respectively.

Table 2.Features extracted from Man original Video

#	Energy	Contrast	Correlation	Homogeneity	Dissimilarity
1	0.025146	210.190504	0.935610	0.261984	7.756421
2	0.023692	259.779760	0.922198	0.242951	8.707179
3	0.024803	220.128348	0.931981	0.254044	7.972318
4	0.023613	283.565735	0.913216	0.238157	9.040883
5	0.023526	283.922083	0.913245	0.237166	9.061196
6	0.024394	253.324017	0.921693	0.246498	8.492463
7	0.023403	287.087647	0.912237	0.235295	9.133428
8	0.023531	283.486981	0.913287	0.236604	9.063333
9	0.023663	281.525429	0.913895	0.238467	9.007324
10	0.023749	277.298614	0.914938	0.238916	8.930641

Table 3.Features extracted from Man spliced Video

#	Energy	Contrast	Correlation	Homogeneity	Dissimilarity
1	0.022339	220.326277	0.947711	0.268442	7.813929
2	0.021079	268.657284	0.937299	0.250757	8.732620
3	0.022023	228.666702	0.945200	0.260421	8.009216
4	0.021672	294.374113	0.928984	0.248458	9.089348
5	0.022208	283.852353	0.931004	0.253649	8.855251
6	0.022049	281.913909	0.931287	0.252369	8.849223
7	0.022029	280.852596	0.931254	0.251559	8.852846
8	0.022803	250.861853	0.937700	0.259962	8.303490
9	0.021919	283.135906	0.930287	0.249667	8.912730
10	0.022059	278.160532	0.931554	0.250508	8.824775

Table 4 and 5 show the energy, contrast, correlation, homogeneity and dissimilarity values extracted from 10 original and copy move images from CoMoFoD dataset.

Table 4.Features extracted from original CoMoFoD image

Image	Energy	Contrast	Correlation	Homogeneity	Dissimilarity
001_O	0.030645	567.038347	0.896041	0.222788	12.978832
002_O	0.017740	344.607450	0.921004	0.178064	10.110350
003_O	0.178863	643.937577	0.946396	0.328368	12.736789
004_O	0.042699	213.863416	0.918373	0.235358	7.039433
005_O	0.042239	216.950946	0.918092	0.233978	7.106022
006_O	0.042339	217.047888	0.918172	0.234360	7.107799
007_O	0.126990	384.379007	0.940857	0.252219	11.073903
008_O	0.038751	165.438976	0.988166	0.317131	5.338411
009_O	0.038751	165.438976	0.988166	0.317131	5.338411
010_O	0.111011	410.001053	0.956322	0.304211	10.035408

Table 5.Features extracted from Forged CoMoFoD image

Image	Energy	Contrast	Correlation	Homogeneity	Dissimilarity
001_F	0.030597	571.685074	0.895605	0.221779	13.033296
002_F	0.017910	321.592494	0.925904	0.179420	9.805903
003_F	0.174918	651.449352	0.945433	0.324857	12.841676
004_F	0.042699	213.688560	0.918111	0.235327	7.038506
005_F	0.042173	212.991662	0.924010	0.233018	7.112381
006_F	0.042244	210.315680	0.924375	0.233451	7.083899
007_F	0.126982	386.535778	0.940556	0.251963	11.110648
008_F	0.038800	165.167339	0.988186	0.317282	5.331791
009_F	0.037342	171.497725	0.987740	0.315378	5.471821
010_F	0.111012	413.702223	0.955957	0.304261	10.062517

Figure 5 shows the scatter plots of energy, contrast, correlation, homogeneity and dissimilarity features for original and copy move (CoMoFoD) images. From the plot we can clearly see that the data points are linearly inseparable.

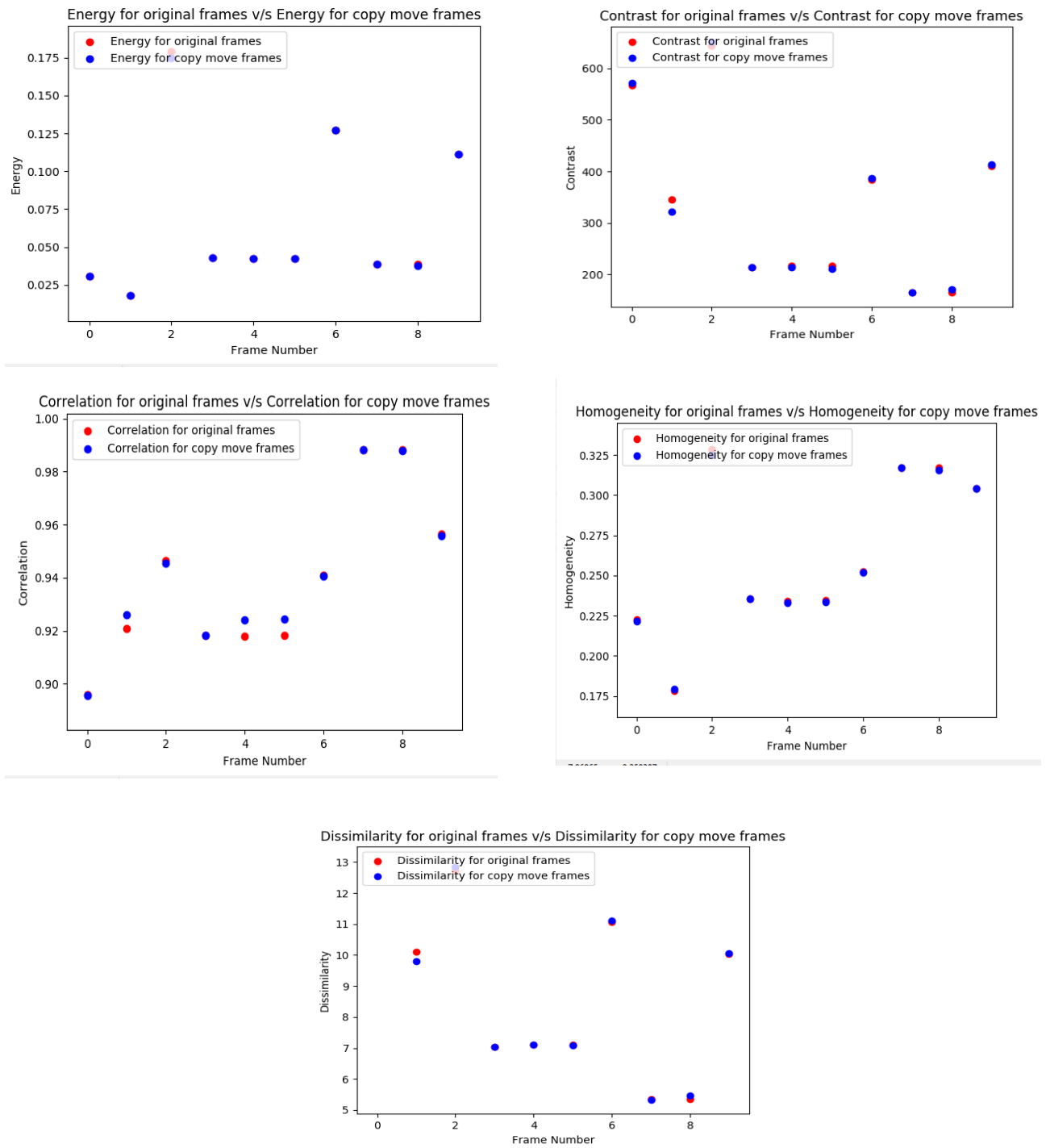


Figure 8. Scatter plots for the features extracted from 25 original and 25 copy move frames from CoMoFoD

Furthermore, Figure 9 shows the scatter plots of energy, contrast, correlation, homogeneity and dissimilarity features for original and spliced images. From the plot we can clearly see that the data points are linearly inseparable

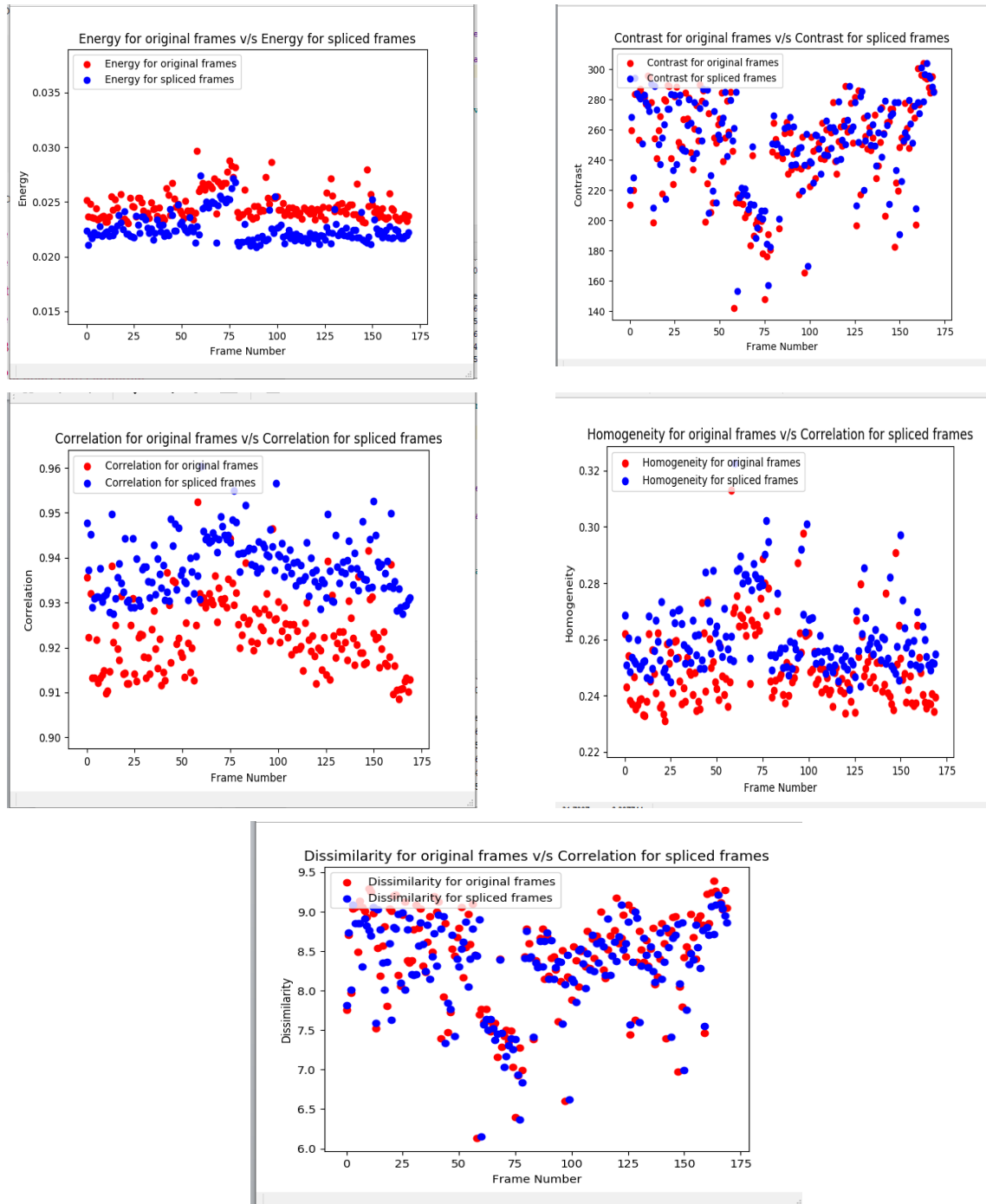


Figure 9. Scatter plots for the features extracted from 169 original and 169 spliced frames from Man video

Table 6 shows the number of frames used from each video (equal number of original and corresponding spliced frames are selected) and the number of original frames whose features values are greater than that of spliced frames. This is obtained by comparing the feature value of the original frame and that of the spliced frame. For example, in the Man video, 200 original and 200 spliced frames are used. 188 out of 200 original frames from Man video have energy value higher than their corresponding spliced frames, while 12 original frames have energy value lower than their corresponding spliced frame. This shows that for any pairs of original and spliced frame the energy value of the original may be greater or less than that of spliced frame. This is true for all five haralick features extracted.

Table 6. Experimental result for original and spliced images

#	Video	Total No. of frames	No. of original frames whose Energy values are greater than that of spliced frames	No. of original frames whose contrast values are greater than that of spliced frames	No. of original frames whose correlation values are greater than that of spliced frames	No. of original frames whose homogeneity values are greater than that of spliced frames	No. of original frames whose dissimilarity values are greater than that of spliced move frames
1	Tank	360	160	85	50	40	109
2	Man	400	188	90	10	28	122
3	Cat	260	77	58	70	48	55
4	helicopter	560	180	120	95	270	30
5	Hen	280	85	62	46	135	14
6	Lion	400	4	199	1	2	200
7	Ufo	180	89	3	89	87	5
8	Tree	460	229	5	227	222	3
9	Girl	300	60	150	8	28	150
10	Dog	360	179	4	178	174	2

The experimental result shows that, out of 1,780 original frames, the energy, contrast, correlation homogeneity and dissimilarity values of 1251, 776, 774, 1034 and 690 original frames are greater than that of their corresponding spliced frames. This means that, the values of these features for original frames are not always greater than or less than that of spliced frames.

Table 7. Experimental result for original and copy move images

#	No of frames (original + copy move)	No. of original frames whose Energy values are greater than that of the copy move frames	No. of original frames whose contrast values are greater than that of the copy move frames	No. of original frames whose correlation values are greater than that of the copy move frames	No. of original frames whose homogeneity values are greater than that of the copy move frames	No. of original frames whose dissimilarity values are greater than that of the copy move frames
1	50	24	0	24	23	0
2	50	1	25	0	0	25
3	50	25	0	25	25	0
4	50	8	21	24	17	20
5	50	23	1	23	24	0

#	No of frames (original + copy move)	No. of original frames whose Energy values are greater than that of the copy move frames	No. of original frames whose contrast values are greater than that of the copy move frames	No. of original frames whose correlation values are greater than that of the copy move frames	No. of original frames whose homogeneity values are greater than that of the copy move frames	No. of original frames whose dissimilarity values are greater than that of the copy move frames
6	50	0	23	0	1	25
7	50	14	0	25	12	1
8	50	25	0	25	25	0
9	50	25	0	0	15	0
10	50	0	25	21	1	24

The results presented in table 7 shows that out of 250 original images only 145, 95, 167, 143 and 95 images have energy, contrast, correlation, homogeneity and dissimilarity values greater than that of their corresponding copy move images. This means that, the values of these features for original images are not always greater than or less than that of copy move images.

5. Conclusion

An experiment is carried out in this paper to see how image splicing and copy move manipulation affect the haralick features of a digital image, with the goal of determining whether these features can be utilized to distinguish between original, spliced, and copy move images. In this experiment, haralick features such as energy, contrast, correlation of original, spliced and copy move images were extracted and compared. The results obtained from the experiment shows that features extracted from original image may be greater or less than those extracted from spliced image. Similarly, the features extracted from original images may or may not be greater than those extracted from images that are affected by copy move forgery. As a result, these features cannot discern between original, spliced, and copy move forged images. Therefore, features that can be used to discern between spliced and original images are needed. Thus in future study, we intend to investigate the effect of splicing and copy move forgeries on other image features that can be extracted.

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