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An Error-Based Statistical Feature Extraction Scheme for Double JPEG Compression Detection

Nivi Varghese[1], Charlse M Varghese[2]

[1, 2]Department of Computer Science and Engineering, KMP College of Engineering, Asamannoor P.O Poomala, Odakkali, Kerala, India

Abstract: ***Discovery of double JPEG compression assumes a critical part in digital image forensics. Some effective methodologies have been proposed to identify double JPEG compression when the essential and auxiliary compressions have distinctive quantization matrices. Be that as it may, identifying double JPEG compression with the same quantization matrix is still a challenging issue. In this paper, an effective error based measurable component extraction plan is displayed to tackle this issue. Initial, a given JPEG document is decompressed to form a reconstructed image. An error image is obtained by figuring the difference between the inverse discrete cosine transform coefficients and pixel values in the recreated image. Two classes of blocks in the error image, to be specific, rounding error block and truncation error block, are analyzed. At that point, a set of features is proposed to characterize the measurable difference of the error blocks between single and double JPEG compressions. At last, the support vector machine classifier is utilized to recognize whether a given JPEG picture is doubly compressed or not. Test results on three picture databases with different quality factors have exhibited that the proposed technique can fundamentally beat the best in class system. Moreover as a part of forensic identification, the network is also trained to detect contrast enhancements being made to the image. Mainly three types of contrast enhancement are detected on image i.e. sigmoid contrast enhancement, linear contrast enhancement and gamma contrast enhancement.***

Keywords: Digital Image Forensics, Double JPEG Compression, Rounding Error, Truncation Error

1. Introduction

With the advancement of image processing technology in the previous decades, digital image altering turns out to be much less demanding without leaving evident visual traces. It is surely understood that JPEG, as a image compression standard, is generally connected in advanced cameras and image processing softwares. Henceforth, the JPEG (Joint Photographic Experts Group) related scientific issues [1] have been accepting more consideration recently.

In this paper we exhibit another powerful strategy that uses error based statistical features (EBSF). Firstly, an error image is formed by computing the difference between the inverse DCT (IDCT) coefficients (i.e., the float values before being truncated to the range [0, 255]) and pixel values during JPEG decompression. Two classes of error blocks in the error picture are characterized, i.e., adjusting and truncation error blocks. In this way, statistical differences between rounding and truncation error blocks between single and double JPEG compressions are described by three subsets of features in both the spatial and DCT areas. At last, under the machine learning system, the extracted features are combined to identify double JPEG compression with the same quantization matrix.

2. Related Work

For distinguishing double JPEG compression with the same quantization network, Huang et al. [2] initially tended to this issue by proposing a novel perturbing thresholding system. They found that when a JPEG picture is compressed again and again the number of diverse JPEG coefficients between the successive two versions will monotonically diminish. In view of this perception, single and double JPEG compressions can be recognized by looking at the number of diverse JPEG coefficients with an image dependent threshold. The threshold is obtained by utilizing an irregular perturbing procedure. That is, a part of JPEG coefficients from the given JPEG image are first arbitrarily chosen, and after that modified by adding 1 or subtracting 1 arbitrarily. At that point, the modified JPEG image is recompressed with the same quantization matrix, and a value is acquired by counting the diverse JPEG coefficients between the given JPEG image and its recompressed version. The above procedure is repeated different times and the resultant values are averaged to be the threshold. In their system, how to decide the proportion of JPEG coefficients to be perturbed is a significant step, and the creators proposed to get the best possible proportion through a try and- error strategy.

Later, Lai and Bohme [3] concentrated on the properties of block union during the repeated JPEG compressions with quality factor 100 (JPEG-100). At that point, based on the examination of block union, the creators introduced forenscic routines to distinguish JPEG-100 compression in grayscale bitmaps, to evaluate the times of JPEG-100 compressions, to recognize the DCT execution, and further to uncover image altering.

3. Overview of the Method

We first analyze the error blocks in JPEG compression. Based on the analysis, we show the statistical differences of the error blocks between singly and doubly compressed images, and then propose a set of features to characterize such differences. Finally, support vector machine (SVM) is adopted to learn the discriminability from the extracted features for detecting double JPEG compression with the same quantization matrix.

In order to maintain the authenticity and originality of a digital image there is a need for digital image forensic techniques to verify image alternations and forged images. Image manipulations like contrast enhancement can be used by the attacker to avoid leaving visual clues after forging an image. Contrast enhancement is mainly to adjust the brightness of the image. Attackers may perform contrast enhancement locally and globally for creating manipulated images. The contrast variations affect the ultimate form of the image. Contrast enhancement is a process that allows image features to show up more visibly by making best use of colors presented on the display device.

On the built database ANN training is applied to identify the type of contrast enhancement done on the images. Three types of contrast enhancements are being identified as a part of forensics identification i.e gamma contrast enhancement, sigmoid contrast enhancement, linear contrast enhancement.

3.1 Error in Jpeg Compression And Decompression

There are three major steps in JPEG compression: discrete cosine transform of 8 × 8 image blocks, quantization of DCT coefficients, and entropy 31 encoding of the quantized DCT coefficients. JPEG decompression is performed in the reverse order: entropy decoding, de-quantization and inverse DCT. There exist three kinds of error during JPEG compression and decompression. The first kind of error is called the quantization error, which occurs in the process of JPEG compression. It is defined as the difference between the float value of the divided DCT coefficient before rounding and its nearest integer value.

Both the second and third kinds of error exist in the process of JPEG decompression. After performing IDCT on the de-quantized JPEG coefficients, the resulting IDCT coefficients which are float values should be rounded to their nearest integers, and truncation is even needed if the rounded IDCT coefficients exceed the range [0, 255]. Accordingly, the difference between the float IDCT coefficient and its rounded integer is called the rounding error (note that it occurs only when the rounded IDCT coefficient falls in the range of [0, 255]); while the difference between the float IDCT coefficient and its truncated integer (i.e., 0 or 255) is called the truncation error.

It is worth noting that the float un-quantized DCT coefficient cannot be obtained, so the quantization error is unavailable. As a result, only the rounding and truncation error can be utilized to discriminate between singly and doubly compressed images with the same quantization matrix

3.2 Analysis of Error Blocks in JPEG Compression

Given a JPEG image, it is decompressed into the spatial domain. Then, the error image is obtained through the procedure as shown in Fig. 1.

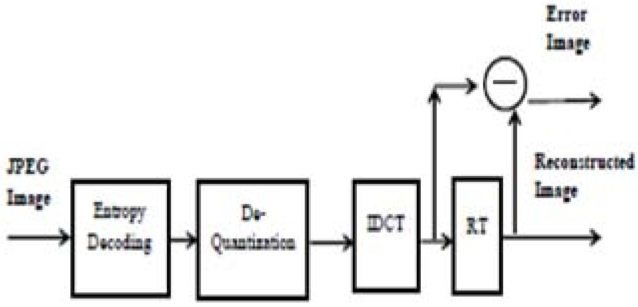

Figure 1: Flow chart of generating the error image in the JPEG decompression process.

3.2.1. Relationship Of Error Blocks Between Two Consecutive Compressions

For the convenience of description, an image that has been JPEG compressed with the same quantization matrix ntimes as an n-times compressed image is being referred. According to the process that generates the error image in Fig. 1, error blocks of an n-times compressed JPEG image, denoted by Rn, can be written as

$$Rn= RT(IDCT(Dn)) - IDCT(\tilde{}Dn)$$

where RT denotes the rounding and truncation operation in JPEG decompression, IDCT denotes the inverse discrete cosine transform, ˜Dn denotes the de-quantized JPEG coefficients during the process of the *n*-times decompression. According to the definition of de-quantization, we have

$$\check{}Dn= Kn \times Q$$

where Q is the quantization matrix and Kn denotes the coefficient matrix of n times compressed image. „x" denotes the component wise multiplication on each pixels.

After each compressions there are certain block values does not varies and such blocks can be called as stable error blocks can be denoted by Mn ,other blocks whose value Mn ≠ 0 are called unstable error blocks. While analysing the error blocks for the detection of double compression these stable blocks will not provide any usefull information so it should be eliminated before computations. In order to distinguish n times compressed image from n+1 compressed image there is a need to focused on the error blocks ,at that time stable error blocks will not provide any information and it should be excluded.

Another important idea is that the unstable error blocks wiil not increase with the increase in the number of compressions, i.e the unstable error blocks reduced as the number of compression increases. The stable error blocks are always stable which will not changes its value during recompressions. From the above analysis two main ideas should be considered here stable error blocks should be eliminated before computation and the decrease in number of unstable blocks indicates that there are only few compressions are occured .

3.2.2 Difference Between Rounding And Truncation Error Blocks:

Two kinds of error (i.e., rounding error and truncation error) occur during JPEG decompression. Accordingly, error blocks can be categorised into two classes, i.e., rounding error blocks and truncation error blocks. A rounding error block is a block whose elements all belong to the range [−0.5, 0.5]; while a truncation error block is a block of which at least one element exceeds the range [−0.5, 0.5]. Let Fn(u, v)denote the (u, v)-th DCT coefficient of an error block Rn, where u, v= 0, · · · , 7. According to the definition of DCT, we have the following formula

Fn(u, v)= DCT (Rn)

If Rn is a rounding error block (denoted by R_n^r), then $|R_n^r(i,j)| \le 0.5$,.i, j = 0, 1, · · · , 7. As a result, the absolute value of the direct-current (DC) coefficients, $|F_n^r$ (0, 0)|, is limited.For the AC coefficients F_n^r (u, v) ((u, v) ≠(0, 0)), similarly we have

$$|F_n^r(u,v)| \le \frac{1}{8}\sum_{i=0}^{7}\sum_{j=0}^{7}\left|\cos\frac{(2i+1)u\pi}{16}\cos\frac{(2j+1)v\pi}{16}\right| \le 8$$

From Eqs. it is seen that $|F_n^r$(u, v) | is upper bounded. Note that Mn= [DCT(Rn)/Q] = [Fn/Q]. With the increase of quantization steps, it is more and more likely that [F_n^r /*Q*] = 0, leading to the decrease of the number of unstable rounding error blocks. If Q(0, 0) >8 and Q(u, v) >16 for (u, v)≠(0, 0), then all round error blocks become stable, and thus there are no unstable rounding error blocks available for discrimination.

In contrast, truncation error can exceed the range [−0.5, 0.5], so the absolute values of the DCT coefficients of a truncation error block (denoted by $|F_n^t$ |) are not constrained by the upper bounds derived above, which means that unstable truncation error blocks can be more resistant to the increase of quantization steps than unstable rounding error blocks. It also implies that the features should be extracted from unstable rounding and truncation error blocks separately due to their intrinsic difference in value range.

According to the above analysis, two rules to extract effective features for discrimination is summarized. First, stable error blocks should be excluded before feature extraction. Second, features should be separately computed from rounding and truncation error blocks.

3.3 Feature Extraction

In this subsection, it is focussed on distinguishing between single and double JPEG compressions. The statistical differences between singly and doubly compressed JPEG images is shown, and then propose a set of features for SVM to discriminate between them.

3.3.1. Statistical Differences Between Singly and Doubly Compressed Images:

To exemplify the statistical differences between single and double JPEG compressions, three image databases are used: the Uncompressed Color Image Database (UCID), the Natural Resources Conservation Service (NRCS) database and the Sun Yat-Sen University (SYSU) database. Note that the SYSU database is the same as “OurLab” database used in. There are 1338 images with size 384 × 512 or 512 × 384 in the UCID database, 1542 images cropped with size 512 × 768 in the NRCS database and 1128 images with size 512 × 512 in the SYSU database.

All these images are converted to gray scale images. Let $max_{(i,j)}(|R_n^{r,l}$ (i, j)|) and $max_{(i,j)}(|R_n^{t,s}$ (i, j)|) denote the maximum absolute values of the l^{th} rounding error block and s^{th} truncation error block, respectively. Similarly, let $max_{(u,v)}(|F_n^{r,l}$(u, v)|) and $max_{(u,v)}$ ($|F_n^{t,s}$(u, v)|) denote the maximum absolute values of DCT coefficients of the lth rounding error block and the sth truncation error block, respectively, where n = 1, 2, i, j = 0, 1, · · · , 7, u, v = 0, 1, · · · , 7.All these statistical values are computed by excluding all stable error blocks.

First, the error blocks of singly compressed images (*n* = 1) exhibit different statistics from those of doubly compressed images (*n* = 2) in both spatial and DCT domains. Second, the statistics of rounding error blocks are considerably different from those of truncation error blocks. Statistical differences also evidently exist between the rounding and truncation error blocks in terms of the average values. It should be specially pointed out that some statistical values of the rounding error blocks are zeros. This is due to the following reason.

When QF is relatively small (such as 60), large steps are applied in coefficient quantization, and unstable rounding error blocks tend to become stable. In some cases, there are no unstable rounding error blocks available for computing the statistical values resulting in the default value “0”. In contrast, unstable truncation error blocks do exist in all of the cases.

In summary, the above two facts imply that rounding and truncation error blocks can provide discriminative information for detecting double JPEG compression, and the two kinds of error blocks show fairly different statistics and thus should be separated for feature extraction . The numbers of rounding and truncation error blocks between single and double JPEG compressions are also different. Note that rounding error is limited to the range of [−0.5, 0.5] while truncation error can exceed this range. It means that rounding error blocks are likely more fragile to JPEG recompression than truncation error blocks.

3.3.2. Error-Based Statistical Features:

It is shown that the error blocks between single and double JPEG compressions exhibit different statistical characteristics. In this subsection, the error-based statistical features (EBSF) are extracted from rounding and truncation error blocks separately for detecting double JPEG compression with the same quantization matrix. The EBSF feature set consists of three subsets. The first subset, denoted by EBSF_spatial, is extracted directly from the error image. It contains the means and variances of absolute error values over the rounding and truncation error blocks. For the rounding error blocks, the mean and variance of absolute error values, denoted by mean($|R^r_n|$) and var($|R^r_n|$), are given by

$$\text{mean}(|R^r_n|) = \frac{\sum_{l=1}^{L}\sum_{i=0,j=0}^{i=7,j=7}\left|R_n^{r,l}(i,j)\right|}{64\ L}$$

$$\text{var}(|R^r_n|) = \frac{\sum_{l=1}^{L}\sum_{i=0,j=0}^{i=7,j=7}\left(\left|R_n^{r,l}(i,j)\right| - \text{mean}(|R^r_n|)\right)^2}{64\ L}$$

where L denotes the number of the unstable rounding error blocks in the error image. For the truncation error blocks, the mean and variance of absolute error values, denoted by mean($|R^t_n|$) and var($|R^t_n|$), can also be calculated in a similar way.

Apart from EBSF_spatial, features from the DCT domain of Rn, i.e., Fn= DCT(Rn), can also capture statistical differences between single and double JPEG compressions. As a variant of F_n,W_n= [F_n/Q] × Q has been found to be more discriminative. W_n can be viewed as the result of performing JPEG compression on the error image R_n followed by de-quantization.

Besides, from Eq. (3.3), the computation of W_n is equivalent to compressing the reconstructed image again and then calculating the de-quantized JPEG coefficient changes between the two consecutive compressions. The second subset of the proposed features, denoted by EBSF_dct, consists of the means and variances of absolute values of W_n over the rounding and truncation error blocks. It is known that the DC and AC components of DCT coefficients have different characteristics, thus, features from the DC and AC components of W_n should also be extracted separately. For the rounding error blocks, the mean and variance of absolute values of the DC components of Wn, denoted by mean($|W^r_n$,D$|$) and var($|W^r_n$,D$|$), can be given by

$$\text{mean}\left(\left|W^r_{n,D}\right|\right) = \frac{\sum_{l=1}^{L}\left|W_n^{r,l}(0,0)\right|}{L}$$

$$\text{var}\left(\left|W^r_n, D\right|\right) = \frac{\sum_{l=1}^{L}\left(\left|W_n^{r,l}(0,0)\right| - \text{mean}\left(\left|W^r_{n,D}\right|\right)\right)^2}{L}$$

where $W_n^{r,l}(u,v)((u,v) \neq (0,0))$denotes the DC component of Wn from the lth rounding error block. The mean and variance of absolute values of the AC components of Wn, denoted by mean($|W^r_{n,A}|$)and var($|W^r_{n,A}|$), are

$$\text{mean}\left(\left|W^r_{n,A}\right|\right) = \frac{\sum_{l=1}^{L}\sum_{(u,v)\neq(0,0)}\left|W_n^{r,l}(u,v)\right|}{63L}$$

$$\text{var}\left(\left|W^r_{n,A}\right|\right) = \frac{\sum_{l=1}^{L}\sum_{(u,v)\neq(0,0)}\left(\left|W_n^{r,l}(u,v)\right| - \text{mean}\left(\left|W^r_{n,A}\right|\right)\right)^2}{63L}$$

where $W_n^{r,1}$ (u, v) ((u, v) ≠(0, 0)) denotes the (u, v)-th AC component of Wn from the lth rounding error block. For the truncation error blocks, the statistical values of the DC and AC components of Wn, including mean($|W^t_{n,D}|$), var($|W^t_{n,D}|$),mean($|W^t_{n,A}|$) and var($|W^t_{n,A}|$), can also be calculated in a similar way.

Note that instead of calculating the means and variance, we can alternatively calculate these statistical values for each of the 63 AC components of Wn, which results in a 252-dimensional feature set. The alternative strategy has the advantage of considering the statistical differences among different AC components. However, by this experiments, it can achieve an improvement only in a few cases, at the cost of a significant increase of feature dimensionality. For the simplicity of SVM training, in this paper prefer to calculate the features of the AC components.

It should be pointed out that both Wn and the feature used in can be computed by performing consecutive JPEG compressions, but they are considerably different. The feature in is the number of different quantized DCT coefficients between two consecutive compressions, whereas Wn is the difference of de-quantized DCT coefficients between two consecutive compressions. Moreover, the method in requires to generate an image-dependent threshold by randomly and slightly modifying some quantized DCT coefficients followed by JPEG compression and decompression multiple times. Whereas, the calculation of Wn does not involve such a process.

The last subset of the proposed features, denoted by EBSF_ratio, contains only one feature. It is the ratio of the number of unstable rounding error blocks, n_r, to the number of all unstable error blocks,n_a, i.e., calculated by n_r/n_a. The ratio n_r/n_a can provide discriminability for detecting double JPEG compression.

In summary, a set of thirteen features, consisting of four features from EBSF_spatial, eight features from EBSF_dct, and one feature from EBSF_ratio, is extracted from each given JPEG image, and the SVM is employed for classification.

3.4 Forensics Identification

In this work, thesis focus on detecting double compressed jpeg images. When altering a JPEG image, typically it is loaded into a photo–editing software (decompressed) and after manipulations are carried out, the image is re–saved (compressed again). The quantization matrix of the unaltered image and the quantization matrix of the re–saved image are identical, then the re–saving (double compressing) operation brings into the image specific changes.

Detecting these changes plays a valuable role in identifying image forgeries. Detecting the traces of double compression also is helpful in other research fields such as steganography. Here, double–compressed images can be produced by some steganographic algorithms. It is important to note that detecting the traces of double compression does not necessarily imply the existence of malicious modifications in the image.

Often images are re–compressed due to reduce the image storage size or transmission time. Furthermore, the image could undergo only simple image adjustment operations such as contrast enhancing. Digital images are widely used for a variety of applications such as governmental, legal, scientific, and military to make critical decisions. Digital images are considered as proofs against various crimes or evidences for various purposes. The aim of image enhancement is to enhance quality of the image so that visual appearance can be improved. By using media editing software such as Photoshop and Picasa, it is easy to alter an image. So, the authenticity and originality of a digital image is no longer believable. So there is a need for digital image forensic techniques in order to verify image alternations and forged images. Image manipulations like brightness and contrast enhancement can be used by the attacker to avoid leaving visual clues after forging an image.

Contrast enhancement is mainly to adjust the brightness of the image. Attackers may perform contrast enhancement locally and globally for creating manipulated images.On the built database ANN training is applied to identify the type of contrast enhancement done on the images. Three types of contrast enhancements are being identified as a part of forensics identification.

3.4.1. Gamma Contrast Enhancement

In the digital era, digital photographs become pervasive and are frequently used to record event facts. Authenticity and integrity of such photos can be ascertained by discovering more information about the previously applied operations. In this thesis, a forensic scheme for identifying and reconstructing gamma correction operations in digital images is being proposed.

Statistical abnormity on image grayscale histograms, which is caused by the contrast enhancement, is analysed theoretically and measured effectively. Gray level mapping functions involved in gamma correction can be estimated blindly. Gamma correction, the widely used contrast enhancement operation, is just a sort of content-preserving manipulation.

3.4.2. Sigmoid Contrast Enhancement

Sigmoid function is a continuous nonlinear activation function. The name sigmoid, is obtained from the fact that the function is "S" shaped. Statisticians call this function the logistic function, Using x for input, f(x) as output and with t as a contrast factor term, the sigmoid function can be given as,

$$f(x)=\frac{1}{1+e^{-tx}}$$

The sigmoid function has the characteristics that it is a smooth continuous function, the function outputs within the range -1 to 1, mathematically the function is easy to deal with; it goes up smoothly and kindly. Figure 2 shows the plot of function f(x) for various values of „t". The input variable „x" varies from -1 to + 1 and the output also lies in the range -1 to +1.

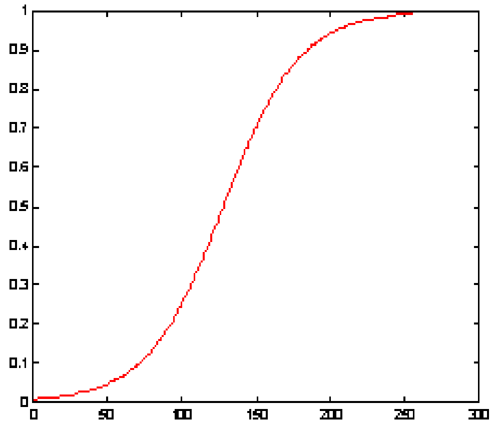

Figure 2: Sigmoid function plotted for various values of „t"

3.4.3. Linear Contrast Enhancement

Linear contrast enhancement, also referred to as a contrast stretching, linearly expands the original digital values of the remotely sensed data into a new distribution. By expanding the original input values of the image, the total range of sensitivity of the display device can be utilized.

Linear contrast enhancement also makes subtle variations within the data more obvious. These types of enhancements are best applied to remotely sensed images with Gaussian or near-Gaussian histograms, meaning, all the brightness values fall within a narrow range of the histogram and only one mode is apparent.

4. Experimental Results

Double JPEG compression detection is an important research topic for digital forensics. A powerful recompression detection method by extending the first digit features is proposed. Based on the analysis of the distribution of the first digits of quantized DCT coefficients, the joint probabilities of the mode based first digits of the quantized DCT coefficients including value zero is extracted as the classifying features to distinguish between singly and doubly compressed images.

Extensive experiments and comparisons with prior state-of-the-art demonstrate that the proposed scheme can detect the double JPEG compression effectively and outperforms the existing algorithms significantly. Moreover, the method can achieve a satisfactory classification accuracy even for the double JPEG compression with quality factor 95 followed by 50 or 55, while many previous works fail in the detection.

All experiments are conducted on the three benchmark databases, i.e., UCID, NRCS and SYSU. All these images are first converted to grayscale images, and singly JPEG compressed with a specific QF to generate negative-class samples. Then the singly compressed images are recompressed with the same QF to generate positive class samples. For each QF, we randomly choose half of the singly and doubly compressed images as the training samples, and the remaining samples are used for testing. For the classifier, the soft-margin SVM with the Gaussian kernel is employed

and the parameters c and γ are determined by a grid-search on the multiplicative grid
$(c, \gamma) \in \{(2^i, 2^j, 2j)|, i \in \{0, 1, \cdots, 20\}, j \in \{-15, -14, \cdots, 3\}\}$.

Each training-testing procedure is repeated over 20 times and the average classification accuracy rate is reported.Moreover as a part of forensic identification, the network is also trained to detect contrast enhancements being made to the image. Mainly three types of contrast enhancement are detected on image i.e. sigmoid contrast enhancement, linear contrast enhancement and gamma contrast enhancement.

5. Conclusion and Future Suggestions

In this paper, a learning based method to detect double JPEG compression with the same quantization matrix is being presented, which is easy to implement while shows promising performance. The error blocks in JPEG compression is first analysed. Based on the analysis, 13-dimensional error-based statistical features were extracted from rounding and truncation error blocks separately. Finally, with the extracted features, the SVM classifier is applied for detecting double JPEG compression. Experimental results demonstrated that the proposed method is superior to the state-of-the-art method on the UCID,NRCS and SYSU databases with various quality factors.

Moreover as a part of forensic identification, the network is also trained to detect contrast enhancements being made to the image. Mainly three types of contrast enhancement are detected on image i.e. sigmoid contrast enhancement, linear contrast enhancement and gamma contrast enhancement. As a part of future enhancement, the network should be trained to detect the location of modifications done on the image.

References

[1] Jianquan, Y., Xie, J., Zhu, G.,Kwong, S.,Shiet, Y.Q., “An Effective Method for Detecting Double JPEG Compression with the Same Quantization Matrix,” IEEE Trans. Information Forensics Security, vol. 9, no. 11, Nov. 2014
[2] F. Huang, J. Huang, and Y. Q. Shi, “Detecting double JPEG compression with the same quantization matrix,” IEEE Trans. Inf. Forensics Security,vol. 5, no. 4, pp. 848– 856, Dec. 2010.
[3] S. Lai and R. Böhme, “Block convergence in repeated Transform coding: JPEG-100 forensics, carbon dating, and tamper detection,” in Proc. IEEE Int. Conf. coust., Speech, Signal Process., May 2013,pp. 3028–3032.
[4] Bianchi, T. and Piva, A., “Detection of non aligned double JPEG compression based on integer periodicity maps, ”IEEE Trans. Inf. Forensics Security, vol. 7, no. 2, pp. 842– 848, Apr. 2012.
[5] Bianchi, T. and Piva, A. “Image forgery localization via block-grained analysis of JPEG artifacts,” IEEE Trans. Inf. Forensics Security, vol. 7,no. 3, pp. 1003–1017, Jun. 2012.
[6] Bohme, R., Lai, S. “Block convergence in repeated transform coding: JPEG- 100 forensics, carbon dating, and tamper detection,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., May 2013,pp. 3028–3032.
[7] Chen,C., Shi, Y.Q. and Su, W., “A machine learning based scheme for double JPEG compression detection,” in Proc. 19th Int. Conf. Pattern Recognit., Dec. 2008, pp.1–4.
[8] Chen, Y.L., Hsu, C.T. “Detecting recompression of JPEG images via periodicity analysis of compression artifacts for tampering detection,” IEEE Trans. Inf. Forensics Security, vol. 6, no. 2, pp. 396–406,Jun. 2011.
[9] De Queiroz, R.L., Fan, Z. “Identification of bitmap compression history: JPEG detection and quantizer estimation,” IEEE Trans. Image Process., vol. 12, no. 2,pp. 230–235, Feb. 2003.1942 IEEE Transactions On Information Forensics and Security,Vol. 9, No. 11, November 2014
[10] Farid, H. “Exposing digital forgeries from JPEG ghosts,”IEEE Trans.Inf. Forensics Security, vol. 4, no. 1, pp.154–160, Mar. 2009.

Author Profile

Nivi Varghese received the B.Tech Degree in Computer Science from Mahatma Gandhi University, Kerala, India, in 2013. She is currently pursuing M.Tech Degree in Computer Science and Engineering with Specialization in Cyber Security from Mahatma Gandhi University, Kerala, India. Her research interests include image processing.

Charlse M Varghese, completed his BE and ME in Computer Science And Engineering. Currently he is working as Asst. Professor at KMPCE.