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Image Modification Detection & Modification Prediction System

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Abstract:
This paper presents a method of image forensics within digital images, the main aim of the paper to detect global image modification and predict the modification type without knowing any previous knowledge about that image. (global modification means image compression, filtering etc) the method we are doing comparing original images and training set images then analyzing modification done or not if modification detected find the type of modification. on this method we use image feature values for detection. the feature values given as in put of the classifier the output gives the image modified or not. from that classifier output distinguish the modification type. This method also applicable for another images format modification detection.

Keywords*: image editing, illusion, deception, hrbd*

1. Introduction

In current scenario many image processing technique are available same way so many image manipulation tools also available. Without any deep knowledge any one can manipulate or make smaller or major difference in original images. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. this paper mainly focus digital images. the digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems.

Image modification is done in different manner that is using many image editing tools. image modification or manipulations also called imaging is the application of image editing techniques to images in order to create an illusion or deception (in contrast to mere *enhancement* or *correction*) after the original image took place.In digital editing, photos are usually taken with a digital camera and input directly into a computer. Transparencies, negatives or printed photographs may also be digitized using a scanner, or images may be obtained from image databases. With the advent of computers, graphics tablets, and digital cameras, the term *image editing* encompasses everything that can be done to a photo, whether in a darkroom or on a computer. image manipulation is often much more explicit than subtle alterations to color balance or contrast and may involve overlaying a head onto a different body or changing a sign's text, for examples. Image editing software can be used to apply effects and warp an image until the desired result is achieved. The resulting image may have little or no resemblance to the photo (or photos in the case of compositing) from which it originated. Today, photo manipulation is widely accepted as an art form.

Technical retouching Manipulation for image restoration or enhancement (adjusting colors / contrast / white balance (i.e. gradational retouching), sharpness, removing elements or visible flaws on skin or materials). Creative retouching Used as an art form or for commercial use to create more sleek and interesting images for advertisements. Creative retouching could be manipulation for fashion, beauty or advertising photography such as pack-shots (which could also be considered inherently technical retouching in regards to package dimensions and wrap-around factors). One of the most prominent disciplines in creative retouching is image compositing. Here, the digital artist uses multiple photos to create a single image. Today, 3D computer graphics are used more and more to add extra elements or even locations and backgrounds. This kind of image composition is widely used when conventional photography would be technically too difficult or impossible to shoot on location or in studio.The image manipulation industry has often been accused of promoting or inciting a distorted and unrealistic image of self; most specifically in younger people. The world of glamour photography is one specific industry which has been heavily involved with the use of photo manipulation (an obviously concerning element as many people look up to celebrities in search of embodying the 'ideal figure').

Image manipulation has triggered negative responses from both viewers and celebrities. This has led to celebrities refusing to have their photos retouched in support of The American Medical Association that has decided to “take a stand against rampant photo retouching, declaring the practice detrimental to your health.[1] These include: Keira Knightley, Brad Pitt, Andy Roddick, Kim Kardashian, and Jessica Simpson.

Britney Spears agreed to release "un-airbrushed images of herself next to the digitally altered ones"[2]. The fundamental motive behind her move was to "highlight the pressure exerted on women to look perfect"[2]. In addition, 42-year old Cate Blanchett also appeared on the cover of "Intelligent Life’s 2012 March/April" issue ; makeup free and without digital retouching for the first time[3].

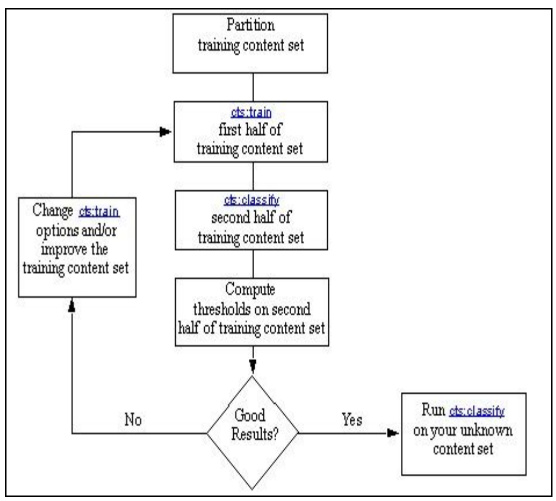
2. System Model

In this paper we propose a simple method of image modification or manipulation detection and find out the type of modifications. we are mainly focus on digilal images that is original true colour images. image compression, image filtering ,colour value change etc are the global modifications. if this kind of any action are carried out then we can detect the type using our method.

The idea behind the system is simple we are extracting some image feature values from the image and find the level of extracted values find that the image is modified or not after that finding which type of modification is done. Another important thing that in this system we have no previous knowledge about the input image that is victim image

In this system we are mainly consider the threshold values of a image and for more accuracy and perfection we consider another two image sets

HRBD the histogram statistics of reorganized block-based discrete cosine transform coefficients and HRBT the histogram statistics of reorganized block-based Tchebichef moments



2.1. Basic Principles

To catch up modification one approach consists in training a classifier which uses as input some image features normally altered by image modifications. Once the classifier trained, one just has to extract these features from one image under investigation and provide them to the classifier for analysis. Efficiency of such an approach largely depends on 1) the design of proper image features, and 2) the way the classifier is built. In this study, in order to only evaluate image feature To catch up modification one approach consists in training a classifier which uses as input some image features normally altered by image modifications. Once the classifier trained, one just has to extract these features from one image under investigation and provide them to the classifier for analysis. Efficiency of such an approach largely depends on 1) the design of proper image features, and 2) the way the classifier is built. In this study, in order to only evaluate image feature performance, we use support vector machines (SVMs) [17]. This choice stands on the fact that SVMs have shown superior classification performances in many applications [18], [19].

In our context, our primary objective is to distinguish modi- fied images from original ones (i.e., not modified). To achieve this goal, we have trained different binary SVM classifiers or dtectors” (e.g., original images versus JPEG modified images, original images versus filtered modified images, and so on) using the threshold values. An image is declared unauthentic, if at least one of these classifiers notifies it. Sec- ond, for the purpose of determining the type of modification, we build a multiclass classifier based on one-versus-one binary classifiers, each of which discriminates images modified accord- ingly to two kinds of possible modifications (e.g., JPEG versus filtering, JPEG versus contrast adjustment, contrast adjustment versus scaling, and so on). By analyzing the responses of these classifiers, a multiclass conclusion is drawn. Among the differ- ent strategies for combining decisions of binary classifiers, the max-wins voting (MWV) is one of the most commonly used approaches [20]. MWV assigns an instance to a class which has the largest votes from all binary classifiers.

2.2. Threshold value setting

Here is the base idea of the paper that is in every digital image have a threshold value. which have a specific level, that means not all the extracted values are not same but a clear levels of values this level we are using here that level. In the classifier we are setting some threshold levels. From a particular level of value considered after that we can detect the image is modified. For finding the type of modification the levels are given in max-wins voting. For more accuracy and perfection we can use HRBD and HRBT this also added in SVM classifier. HRBD [8] and HRBT features are extracted following the same strategy. Their difference stands in the image "transformed" coefficients considered the DCT coefficients for aim at carrying out the variations of the histograms of groups of such DCT coefficient or moments. Notice that some of these features have been previously experimented in the spatial [21] and wavelet [22], [23] domains.

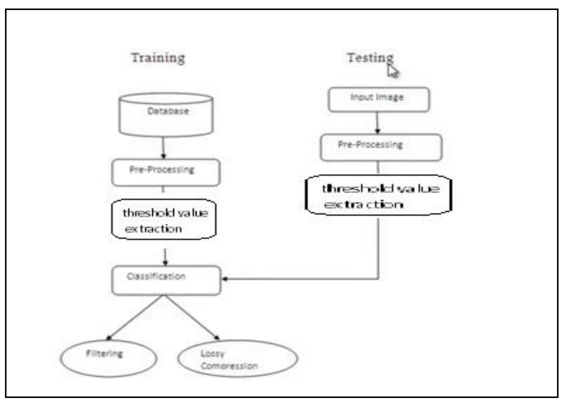
3. Experimental Setup

The first step of the project is we have to train the training classifier. for that There are two basic steps to using the classifier: training and classification. *Training* is the process of taking content that is known to belong to specified classes and creating a classifier on the basis of that known content. *Classification* is the process of taking a classifier built with such a training content set and running it on unknown content to determine class membership for the unknown content. Training is an iterative process whereby you build the best classifier possible, and classification is a one-time process designed to run on unknown content.

The basic idea is that the classifier takes a set of training content representing known examples of classes and, by performing statistical analysis of the training content, uses the knowledge gleaned from the training content to decide to which classes other unknown content belongs. You can use the classifier to gain knowledge about your content based on the statistical analysis performed during training.

For the training set we have to make data set which contains many images. The successful result we have to make a correct order of image selection and all images in the set must be same dimension.

Then the image converted into greyscale mode the give to training set. After that find the threshold values of different images, from this values classifier give the result that the image is modified or not if modification detected then finding the modification type , that done within MWV step which gives some levels and which is the possible modification.



4. Experimental results

4.1. Image Test Sets and Modifications

Four test sets of images issued from different medical image modalities were considered.

- 120 images of 12 bit depth and of 256×256 pixels from three patients.
- 200 images with 512 × 512 pixels coded on 12 bits.
- imaging: 162 4740 × 3540 pixels coded on 12 bits from multiple patients.
- imaging (echo): 52 images of 576 × 690 pixels and 8-bit

The modifications we have considered in these experiments are contrast and brightness adjustment, Gaussian filtering, scal- ing, Laplacian filtering, JPEG and JPEG2000 lossy compression, and histogram equalization. Table I gives the parameters used for each of these modifications

Table I gives the parameters used for each of these modifications.

For each modality, the different image test sets were divided into two groups for training and testing our classifiers (see Sec- tion II-A). Next, we give the average results achieved with clas- sifiers that have been trained several times (at least ten times) with different fold-cross validation (i.e., training and testing sets are randomly selected at each trial). SVM classifiers were used so as to only evaluate performance of HRBD and HRBT feature or of their combination. Notice that features are extracted

DETECTION RATES—MODIFIED VERSUS NONMODIFIED IMAGES

Detection rate (%)	MRI	Mammography	CT	Echography
HRBT	78.51	84.84	83.21	81.65
HRBD	78.26	84.49	82.47	84.67
HRBT&HRBD	79.13	85.67	85.06	85. 87

MULTICLASSCLASSIFIER DETECTION RATES BASED ON HRBT/HRBD/HRBT&HRBD FEATURES

Detection rate (%)	MRI HRBT/ HRBD/ HRBT& HRBD	Mammo. HRBT/ HRBD/ HRBT& HRBD	CT HRBT/ HRBD/ HRBT& HRBD	Echography HRBT/ HRBD/ HRBT& HRBD
JPEG2K	78.53/83.56/ 84.99	71.38/82.59/ 85.56	86.38/90.94/ 92.93	93.75/85.05/ 96.92
JPEG	79.47/99.01/ 98.37	83.84/89.75/ 98.02	89.17/63.37/ 93.60	98.56/98.08/ 99.78
Gaussian filtering	75.17/77.00/ 77.62	81.60/86.79/ 89.14	78.04/69.40/ 79.30	86.15/76.72/ 87.85
Laplacian filtering	100/100/ 100	100/100/ 100	100/100/ 100	100/100/ 100
Scaling	72.31/79.23/ 80.69	81.00/86.17/ 89.75	81.39/75.52/ 83.60	86.73/86.57/ 91.92
Brighten	68.56/73.54/ 74.14	65.87/70.27/ 73.12	73.52/57.15/ 76.50	75.73/72.93/ 77.52
Contrast	59.85/82.08/ 83.23	59.56/62.52/ 66.64	73.14/78.15/ 79.38	63.78/67.71/ 69.23
Histeq.	100/100/ 100	100/100/ 100	100/100/ 100	100/100/ 100

Notice also that the parameters of the SVM were selected from their receiver operating characteristic curves.

4.2. Performance Evaluation

As mentioned previously, one first objective is to discriminate original images from modified ones. Once an image is declared unauthentic, a multiclass classifier is exploited to distinguish the nature of the modification. Due to paper length limitation, only the detection rate is used as performance indicator; rates that are listed in Tables II and III are for HRBD and HRBT features and for their combination As mentioned previously, one first objective is to discriminate original images from modified ones. Once an image is declared unauthentic, a multiclass classifier is exploited to distinguish the nature of the modification. Due to paper length limitation, only the detection rate is used as performance indicator; rates that are listed in Tables II and III are for HRBD and HRBT features and for their combination.

From Table II, it can be viewed that both HRBD and HRBT features can be used for image modification detection. They have similar performances with detection rates about 80% what- ever the image modality. From our experiments, HRBT fea- tures perform better than HRBD features for X-ray image (mammography and CT images). According to our previous comments (see Section II), one reason may stand in the fact that X-ray images have sharp boundaries. Notice also that the false positive and negative detection rates achieved by our bi- nary classifiers are similar and lower than 20%, which is a good tradeoff. The combination of HRBD and HRBT into a single feature set gives better performance. This is in agreement with a result shown by Bayram et al. [15]: detection performance with several sets of image features is better or at least equal to those obtained considering these feature sets independently. However, the gain is rather small and can be explained by the close mathematical relationship of HRBT and HRBD features. In Table III, we give the correct identification rates of the modification considering images declared unauthentic at the previous stage. In general, it can be seen that the modification can be identified with a rate higher than 70% for HRBT and HRBD or than 77% if these features are considered jointly, ex- cept for contrast and brightness adjustment. One reason may stand in the fact that these two modifications confuse our mul- ticlass classifier. If one of these modifications is omitted in the experiment, the detection rate is higher (greater than 78%). Table III also points out that HRBD features perform better than the HRBT for MRI and mammography images but not for CT and echography images. This underline that HRBT and HRBD features put in evidence different pieces of image information that are more or less sensitive to image modifications. It appears that HRBD and HRBT are complementary features. As exam- ple, HRBD features perform better for identifying JPEG images but not for CT images where HRBT features provide better re- sults. This is also supported by the better detection rates we
obtain when HRBD and HRBT are exploited simultaneously. From the aforementioned experiments, where image features are extracted from a single block of 128 × 128 pixels centered into the image, one can expect detecting image processing ap- plied locally. However, detection rates will decrease with the size of the block on which the analysis is conducted. For instance, in the case classifiers are trained based on features extracted from one 32 × 32 pixel block (instead of 128 × 128), the detec- tion rates for discriminating original images (or original pixel blocks) from modified ones fall in the range 74–81% whatever the image modality. These rates are about 5% less than with a block of 128 × 128 pixels (see Table II).

Actually, our system keeps limited to the detection or iden- tification of "*a priori* known" modifications. In the case of an "unforeseen attack," this one will be identified as the modi- fication that leaves the most similar footprint into the image. Nevertheless, our solution can be easily updated. It does not require to recompute and store a new image signature.

5. Conclusion

In this paper, we have shown that image forensics approaches, initially proposed for general public images, can also be used in any imaging. Without taking care of the signal specificities, good detection rates are already achieved. We have also shown that threshold, originally proposed for natural image steganalysis, complemented with new HRBT features can serve blind detection of global image modification and, furthermore, for determining the nature of the modification one image may have undergone. At least, this experiment points out that image moment theory can be exploited for verifying the integrity of images. Future works will focus on identifying more appropriate image moments as well as on the detection of local image modification.

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