

# DETECTING THE COMPOSITE OF PHOTOGRAPHIC IMAGE AND COMPUTER GENERATED IMAGE COMBINING WITH COLOR, TEXTURE AND SHAPE FEATURE

<sup>1</sup>YONGZHEN KE, <sup>2</sup>WEIDONG MIN, <sup>3</sup>XIUPING DU(\*), <sup>4</sup>ZHENWEI CHEN

<sup>1,2,4</sup> School of Computer Science and Software Engineering, Tianjin Polytechnic University, China

<sup>3</sup> School of Internet Education, Tianjin University, China

E-mail: <sup>1</sup>[keyongzhen@tjpu.edu.cn](mailto:keyongzhen@tjpu.edu.cn), <sup>2</sup>[minweidong@tjpu.edu.cn](mailto:minweidong@tjpu.edu.cn), <sup>3</sup>[duxiping@tju.edu.cn](mailto:duxiping@tju.edu.cn)

## ABSTRACT

With the development of computer graphic techniques and smaller visual difference between photographic images (PG) and computer graphics (CG), splicing of computer graphics and photographic is becoming more common, which causes the need for automatically distinguishing computer generated images from real photographs. Based on several visual features that derived from color, texture and shape feature, using posterior probability support vector machine (PPSVM), this paper presents a method for classification of photographic image and computer generated images, and detection of local forgery composite of them. These features are obtained from 800 computer generated images and 800 photographs, and used to train and test the image samples with the PPSVM. The PPSVM can calculate the probability of image belonging to photographic images or computer generated images. We can achieve the result of classification by setting a threshold of probability. The classification accuracies for color, texture and shape features are 76.75%, 85.25% and 69% respectively. The accuracy is improved to 89.375% with combined color, texture and shape features. The proposed classification method is used to detect the local forgeries composite of the CG elements in photographic, and vice visa. Experimental results show that the proposed method is efficient with good detection rate of local forgeries composite of the PG and the CG. It also possess low dimensional features and low time complexity.

**Keywords:** *Photographic Image, Computer Generated Image, Composite, Color, Texture, Sharp Feature, Posterior Probability Support Vector Machine*

## 1. INTRODUCTION

Advances in computer graphics have made it easier to generate photorealistic images, which look very fantastic and beautiful, just like the life in the movie Avatar which is hard to arrange in real world. The composite technology of photographic and computer graphic brings us wonderful visual enjoyment, and may also be used to forge image for cheating others. If the faked images are abused, it may potentially lead to severe social, legal or privacy issues. Apparently it is urgent and also challenging to find effective methods to differentiate them. Photorealistic computer graphics are becoming more and more perceptually indistinguishable from photographic images. However, perceptual indistinguishability between photographs and photorealistic images does not imply complete indistinguishability. Even the most sophisticated rendering algorithms are based on rough models of the real world where photographs are produced through complex interactions among

objects, photons, and imaging devices, let alone simplistic ones that only aim at perceptual realism. The deviation of the computer simulating process from the real-world physics results in statistical differences between photographs and photorealistic images. If we find appropriate image features that capture the differences between photographic and computer graphic, we can design a two-class classifier to distinguish them.

In this paper, we extract feature sets combined with color, texture and sharp feature, and apply the posterior probability support vector machine (PPSVM) to detect the local forgery composite of computer graphics (CG) and photographic images (PG). The posterior probability support vector machine can calculate the probability of one image belonging to photographic images or computer generated image. Through adjusting the threshold of probability, we can obtain better accuracy of detection of local forgery.

This paper is organized as follows. Section 2 presents the related works. The feature extraction method is described in section 3. The classification and detection of local forgery based on PPSVM are introduced in section 4 and 5. Experimental results are discussed in section 6. Finally, conclusion is drawn in section 7.

## 2. RELATED WORK

Recently, researchers have come up with some effective methods aiming at distinguishing the PG and the CG. Farid[1] uses a statistical model based on first four order wavelet statistics to capture regularities inherent to photographic images. A three level quadrature mirror filter (QMF) is computed, where the numbers of features is 72D per color channel, and henthforth 216D features is formed in total considering three color channels. T. T. Ng et.al [2] gives an image model based on geometry, which revealed certain physical differences between the two categories, such as the gamma correction in the PG and sharp structures in the CG. The 192D geometry features are extracted from each image. In literature [3], the authors found that sensor pattern noise can be served as unique identification fingerprint of the images. The pattern noise can be obtained from images using a denoising filter. The paper [4] pointed that image acquisition in a digital camera is fundamentally different from the generative algorithm deployed by computer generated image. Pattern noise introduced by different digital cameras may have common properties, but this common characteristic will not be present in computer graphics. So the pattern noise can be used to identify the differences between the CG and the PG. Ying Wang and Pierre Moulin [5] proposed a very efficient method by extracting 144-dimensional (144-D) feature vector from characteristic functions of wavelet histograms. Statistics of the most significant digits are extracted from image's Discrete Cosine Transform (DCT) coefficients and magnitudes of image's gradient in literature [6].

Beside the challenge of the classification of the PG and the CG, the composition of the PG and the CG is also a challenge for the authenticity of digital images, i.e., how to judge whether objects created by computer graphics software are inserted in natural images, or vice versa. So we can't simply say that the image is the PG or the CG, but we may find out that some small blocks in the image are the CGs and others are the PGs. Conotter[7] develop a method based on wavelet transform domain features as described in literature [1] and sophisticated

pattern noise statistics to detect local forgeries composite of the CG in the PG. The total dimension of features is as many as 228D.

## 3. FEATURE EXTRACTION

As we know from previous works [2][5] [8] [9], the main characteristics of CG generated with basic algorithms are that they have simple scenes without much depth, few and simple colors, patches of uniform color, strong black edges, containing text, and simple textures. Besides, CG often have a plastic/rubber feel because of a lack of details such as dust and small defects, subtle color variation, and radiosity caused by indirect lighting or specularly caused by light sources. Based on the above characteristics, this paper extracts color, texture and shape features for input of classifier.

### 3.1. Color Features

Color feature is the most widely used visual feature in image processing. The main reason is that color is often relevant to the object or scene which is contained in the image. In addition, color is less dependent on the size, direction and angle of the image itself with other visual features compared with other visual features. So it has a high robustness. The common methods to describe the color characteristics include color histogram, color moment, color sets, color aggregation vectors, as well as color features such as color correlative representation methods.

Stricker and Orengo [10] used color moments as feature vectors for image retrieval. Since any color distribution can be characterized by its moments, and most information is concentrated in the low-order moments, only the first moment (mean), the second moment (variance) and the third moment (skewness) are taken as features in this paper.

The HSV color space is a non-linear transform of the RGB-cube. It is widely used in the field of color vision. The chromatic components hue, saturation and value correspond closely with the categories of human color perception. So, we obtain a 3-dimensional feature vector for each channel of HSV color space.

### 3.2. Texture Features

Texture feature is another visual characteristic which does not depend on the color or brightness to response the homogenous image. It is the inherent characteristic of the object surface. The texture feature contains the important information of the object surface about how to organize and arrange the structure and the linkages with surrounding environment. Tamura texture feature, local binary

pattern (LBP), wavelet transform and co-occurrence matrix are the common used texture features.

$$LBP_{p,R}(x,y) = \sum_{i=0}^{p-1} S_{LBP}(p_i, p_c) \times 2^i \quad (3)$$

**3.2.1. Gray-level co-occurrence matrix [11]**

One of the most popular and powerful ways to describe texture is gray-level co-occurrence matrix (GLCM). Co-occurrence matrix can be defined as the co-occurrence of the intensity value at a particular instance and at a particular angle. Features consist of energy, entropy, contrast and correlation are computed from gray level co-occurrence matrixes in four directions (0°, 45°, 90°, 135°) in this paper.

$$CS-LBP_{p,R,T}(x,y) = \sum_{i=0}^{(p/2)-1} S_{CS-LBP}(p_i, p_{i+(p/2)}) \times 2^i \quad (4)$$

where (x,y) denotes the coordinates of a pixel.

It is clear that the LBP produces 256 (2<sup>8</sup>) different binary patterns, whereas the CS-LBP produce only 16 (2<sup>4</sup>) different binary pattern for 8 neighbors.

**3.2.2. Tamura texture feature [12]**

Coarseness, contrast and directionality of tamura texture feature have considerable effects on image analysis. Coarseness is the degree of coarseness of the image. Contrast refers to the level of contrast between image colors. A larger contrast value indicates higher and more evident variations between colors. Directionality can generally describe the degree of directional variation of a certain color. A larger value of directionality indicates a higher degree of directional variation of the color.

**3.3. Shape Features**

The shape of objects and regions is another important feature to express the image information. Generally speaking, there are two methods to represent the shape features. One is the contour feature. The other is the region character. The former uses only the outer boundary of objects, while the latter relates to the shape of the whole region.

**3.2.3. Local binary pattern [13]**

The LBP texture analysis operator is defined as a grayscale invariant texture measure, derived from a general definition of texture in a local neighborhood. For each pixel in an image, a binary code is produced by thresholding its value with the value of the center pixel. A histogram is created to collect up the occurrences of different binary patterns. The basic version of the LBP operator considers only the eight neighbors of a pixel and produces rather long histograms (256). In literature [14], Heikkilä introduced the CS-LBP operator for region description which is more efficient than LBP.

HU invariant moments are put forward by M.K.Hu[15]. It is an invariant moment algorithm, and has the stability characteristics in condition of translation, rotation and zoom. At present, the invariant moments have become important characteristics and are widely used in image recognition. It mainly represents geometrical characteristics of the object's shape. The first order moment is relevant to shape. The second order moment shows the expansion degree of the average, and the average comes from the curve which is around linear. The third order moment is about the measurement of average's symmetry.

The scheme functions of LBP and CS-LBP are given together as

For digital images, we assume the image's gray distribution is f(x, y), after discrete, the (p + q) order ordinary moments and center moments' formulas as follows:

$$S_{LBP}(p_i, p_c) = \begin{cases} 1, & p_i > p_c \\ 0, & otherwise \end{cases} \quad (1)$$

$$m_{pq} = \sum_{x=1}^M \sum_{y=1}^N x^p y^q f(x, y) \quad (5)$$

$$S_{CS-LBP}(p_i, p_{i+(p/2)}) = \begin{cases} 1, & p_i - p_{i+(p/2)} > T \\ 0, & otherwise \end{cases} \quad (2)$$

$$\mu_{pq} = \sum_{x=1}^M \sum_{y=1}^N (x-x_0)^p (y-y_0)^q f(x, y) \quad (6)$$

Where p,q=0,1,2,...

The normalized center moment:

$$y_{pq} = \frac{\mu_{pq}}{\mu_{00}^r} \quad (7)$$

where  $r = \frac{p+q+2}{2}$ , p+q=2,3,...

where  $p_i, p_{i+(p/2)}$  and  $p_c$  correspond to the gray-level of center-symmetric pairs of pixels and the center pixel on a circle of radius R, T is the threshold for the CS-LBP descriptor. The binary pattern of LBP and CS-LBP are calculated as

Formula (5) and Formula (6) directly use ordinary moments or center moments to represent shape feature. This makes the features instable in

the condition of translation, rotation and zooms at the same time. If we use the normalized center moment, the shape feature not only has stability in translation, but also has in zoom.

HU invariant moments use the second order moment and the third order to construct seven invariant moments. They keep translation, zoom and rotation invariant in continuous image, with the formulas as follows:

$$HU_1 = y_{20} + y_{02} \quad (8)$$

$$HU_2 = (y_{20} + y_{02})^2 + 4y_{11}^2 \quad (9)$$

$$HU_3 = (y_{30} + 3y_{12})^2 + (3y_{21} - y_{03})^2 \quad (10)$$

$$HU_4 = (y_{30} + y_{12})^2 + (y_{21} + y_{03})^2 \quad (11)$$

$$HU_5 = (y_{30} - y_{12})(y_{30} + y_{12})[(y_{30} + y_{12})^2 - 3(y_{21} + y_{03})^2] + 3(y_{21} - y_{03})(y_{21} + y_{30})[3(y_{30} + y_{12})^2 - (y_{21} + y_{03})^2] \quad (12)$$

$$HU_6 = (y_{20} - y_{02})[(y_{30} + y_{12})^2 - (y_{21} + y_{03})^2] + 4y_{11}(y_{30} + y_{12})(y_{21} + y_{03}) \quad (13)$$

$$HU_7 = 3(y_{21} + y_{03})(y_{30} + y_{12})[(y_{30} + y_{12})^2 - 3(y_{21} + y_{03})^2] + (y_{30} - 3y_{12})(y_{21} + y_{30})[3(y_{30} + y_{12})^2 - (y_{21} + y_{03})^2] \quad (14)$$

### 3.4 Feature Fusion

In order to improve the performance, several features fusion is used in this paper. First, third-order statistical moments of HSV color space with 9 dimensions is extracted. Second, features such as energy, entropy, contrast and correlation are the most important texture features of image. So 16D features consist of energy, entropy, contrast and correlation are computed from gray level co-occurrence matrixes in four directions. Third, we extract histogram feature of the CS-LBP with 16 dimensions, instead of the traditional LBP features with 256 dimensions. Forth, tamura texture features includes coarseness, contrast, directionality, regularity and linelikeness etc. But only three important features such as coarseness, contrast and directionality are used in our method. Last, Hu invariant moment features are considered to be a description of the statistical characteristics of the image's shape. Seven features including second order and third order of Hu invariant moment are obtained to describe the shape of the image in our method. The process of feature extraction is shown in Figure 1. In summary, the proposed method computed 51D features including 9D color features, 16D GLCM features, 16D CS-LBP features, 3D Tamura texture features and 7D Hu moment invariant features.

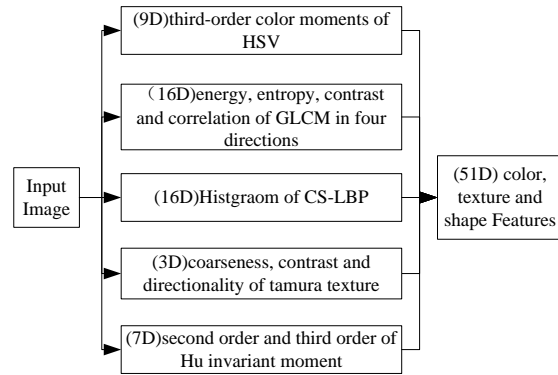


Figure 1: The Process of Feature Extraction

## 4. CLASSIFICATION BASED ON POSTERIOR PROBABILITY SUPPORT VECTOR MACHINE

The posterior probability support vector machine (PPSVM) is used for the automatic classification in this paper. The PPSVM has shown good performance in pattern recognition.

### 4.1. Posterior Probability Support Vector Machine

Platt[16] provided a kernel method where a standard SVM plus sigmoid is trained to yield a posterior probability. A sigmoid is fit to map standard SVM outputs to posterior probabilities, and the sparseness of SVM is still retained. The PSVM maintains comparable performance with that of standard SVM.

Given training data  $x_i \in R^n, i = 1, \dots, l$ , labeled by  $y_i = \{1, -1\}$ , the binary Support Vector Machine (SVM) obtains a decision function  $f(x)$  so that  $\text{sign}(f(x))$  is the prediction of any test data  $x$ .

Instead of predicting the label, many applications require a posterior class probability  $p(y=1|x)$ . The literature [16] proposes to approximate  $p(y=1|x)$  by a sigmoid function

$$P(x) = \frac{1}{1 + \exp(Af(x) + B)} \quad (15)$$

with parameters A and B. To estimate the best values of (A,B), any subset of  $l$  training data ( $N_+$  of them with  $y_i = 1$ , and  $N_-$  of them with  $y_i = -1$ ) can be used to solve the following maximum likelihood problem:

$$\min_{z=(A,B)} F(z) \quad (16)$$

Where

$$F(z) = -\sum_{i=1}^l (t_i \log(p_i) + (1-t_i) \log(1-p_i)), \quad (17)$$

$$p_i = \frac{1}{1 + \exp(Af_i + B)}, f_i = f(x_i)$$

$$t_i = \begin{cases} \frac{N_+ + 1}{N_+ + 2} & \text{if } y_i = 1 \\ \frac{1}{N_- + 2} & \text{if } y_i = -1 \end{cases}, i = 1, 2, \dots, l$$

**4.2 The Procedure of Classification**

The procedure of classification is shown in figure 2. First, Features of every image extracted from image database as the training sets are sent to the PPSVM classifier initially for training (to learn the

pattern) and for predicting the labels of unknown samples once the training is complete. Second, features of testing images are fed into the PPSVM trained classifier, resulting in a probability of image belonging to photographic images or computer generated image. Compared with the output of standard SVM of label “1” or “-1”, the output of PPSVM is a probability value. These testing images belonging to photographic images will have a high probability, and vice versa. By setting a threshold between 0 and 1, testing images can be divided into two categories. If the probability of one image is greater than the threshold, this image belongs to the category of photographic images, and vice versa. We can achieve better results by adjusting the threshold.

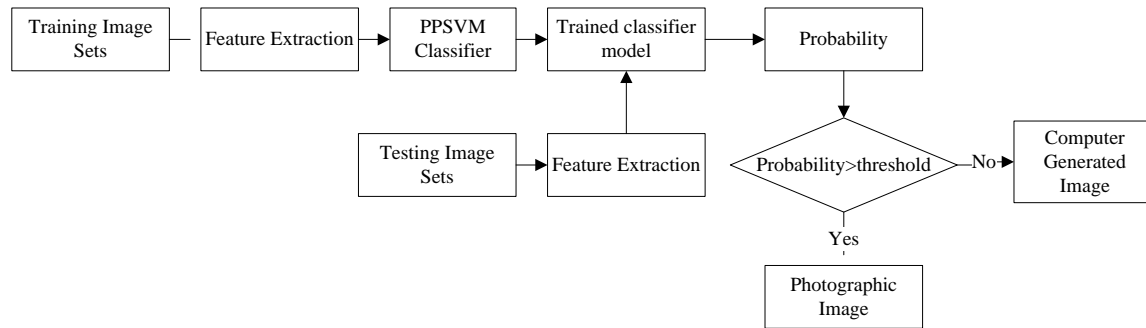


Figure 2: The Procedure of Classification

**5. DETECTING THE COMPOSITE OF PHOTOGRAPHIC IMAGES AND COMPUTER GENERATED IMAGES**

While the classifiers in general perform well on images belonging to a clear-cut category, there is a group of images that confuse the classifiers. This group includes both photographs with graphic content embedded in 3-D real-world scenes and images composed using both photographic and the CG elements [17]. Based on our proposed classification method, we try to detect local forgeries that composite of the CG elements in photographic, and vice visa.

Each spliced image is firstly divided into overlapping blocks with size of n\*n. As a result, we can get (M-n)\*(N-n) blocks for an M\*N pixels image. Then, features extracted from each block based on our feature extraction method mentioned above will be sent to the trained PPSVM. Finally, we can find out the forgery area by marking these blocks with different colors according to the probability.

**6. RESULTS AND DISCUSSION**

**6.1. Image Dataset**

In the experiment, we used 800 photographic images in the Columbia Image Dataset [18] and 800 computer graphics (download from irtc.org) with different level of photorealism. All images are colored, compressed JPEG, and of different size. The scenes of the images have a wide range including indoor and outdoor scenes with landscape, persons, and objects.

**6.2 Classification Performances**

The Least Squares Support Vector machine (LSSVM) classifier with RBF kernel was employed in the experiment. We used the “grid-search” method to find the optimal parameters σ and γ of RBF kernel. To train the LSSVM classifier, we randomly selected half of the images (400 PGs and 400 CGs) as training sets, and the rest of the images (400 PGs and 400 CGs) are used as testing sets.

In our experiments, we compare classification performance of different features under the same experimental conditions. Besides, we made comparisons with previous works [3][19]. Here, we implement these algorithms by ourselves, then train



and test by using the same classifier and parameters in this paper based on our image database. Difference-histograms feature in our experiments achieves accuracy rate of 86.25% which is lower than accuracy rate of 94.3% in [19]. The reason may be that we use different classifier and different image database. The results are shown in table 1.

Table 1: Classification Results with Different Features

Different Characteristics	Feature Dimension	Accuracy Rate
Third-order Moments of HSV color	9D	76.75%
GLCM Features	16D	72.25%
Tamura Texture Features	3D	70.125%
Hu Invariant Moments	7D	69%
CS-LBP	16D	81.25%
Pattern Noise Features[3]	12D	66.25%
Difference-histograms Features[19]	56D	86.25%

We also combine several features to construct a more robust classifier. The results are shown in table 2.

Table 2: Classification Results Combining Different Features

Combination of features	Feature Dimension	Accuracy Rate
GLCM + Tamura texture	19D	79.75%
GLCM + Tamura texture + Hu invariant moment	26D	82.25%
GLCM + Tamura texture + Hu invariant moment + CS-LBP	42D	86.625%
GLCM + Tamura texture + Hu invariant moment + CS-LBP + Color Moments	51D	89.375%
GLCM + Tamura texture + Hu invariant moment + CS-LBP + Color Moments + Differential histogram	107D	94.125%

From the table 2 and table 3, we can find that accuracy rate of 51 dimension features combined with color moment, GLCM, Tamura texture, Hu invariant moment and CS-LBP is 89.375%, higher than 86.25% of 56 dimension differential histogram feature. Further, classification accuracy rate combined with all the features including differential histogram features, color moment, texture features and shape features will reach 94.125%. According to the experimental results, it shows that features combined with color, texture and shape are effective in distinguishing the photographic images and computer generated graphics.

At the same time, we made a comparison between the PPSVM and the standard SVM. Classification accuracy of the PPSVM can be further improved through adjusting the threshold T. As shown in figure 3, when threshold T is 0.41, the classification accuracy reached 93.875%, greater than 93.125% of the standard SVM.

### 6.3 Detecting the Composite of Photographic Images and Computer Generated Images

We used proposed method to detect local forgeries composite of the PG and the CG in our experiments. Test image is divided into overlapping blocks with size of  $n \times n$  ( $n$  is 128 in our experiments). Features of each block including color moment features, gray level co-occurrence matrix features, Tamura texture features, Hu invariant moment features, histogram features of CS-LBP and Differential histogram features are extracted and sent to the trained PPSVM model, and then we can obtain the probability of each image block belonging to photographic image. An example of composite image is shown in figure 4, the output result of the PPSVM classifier is shown in figure 5. Red color indicates that the probability close to 1, and blue color indicates that the probability close to 0. Blue area is considered as computer generated graphic area, and red area is considered as photographic images area. In order to show the test results in the spliced images intuitively, after selecting a threshold T, the corresponding position in spliced image where likely belongs to computer generated image, is marked with white color if probability value is less than T. Figure 6 shows different detection results with different threshold T. Because we use the way of dividing images into small blocks, these blocks in the edge of spliced area will include both photographic image and computer graphics, which will cause certain mistake when using the standard SVM. However, the mistake in the edge of spliced

area can be reduced by adjusting the threshold of probability of PPSVM output.

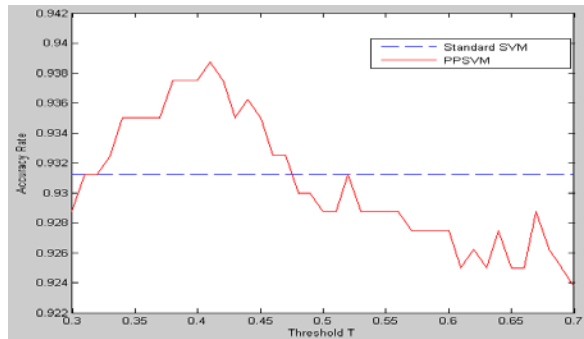


Figure 3: Comparison between the PPSVM and the Standard SVM



Figure 4: Example of Composite Image

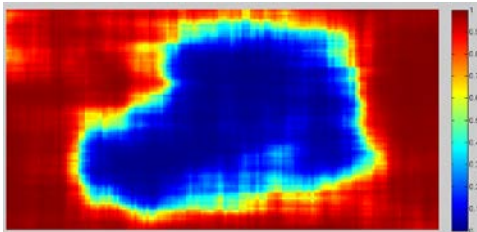


Figure 5: Probability of Different Area

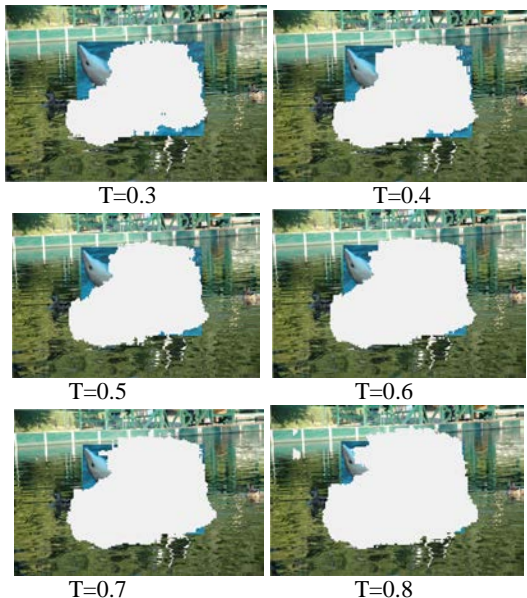


Figure 6: Experimental Results with Different Threshold

## 7. CONCLUSIONS

Based on the main characteristics of CG, several features such as color, texture and shape features are extracted in this paper. Then, those features are fed into the PPSVM for training and testing to generate the probability of one image belonging to photographic images or computer generated image. By adjusting the threshold of probability, we can achieve better results of classification and good performance on detection of local forgeries composite of photographic image and computer generated image. The experimental results demonstrate that our method is efficient with high detection accuracy. The future work is to extract more other features about color, texture and shape, and then obtain best combinations of all the features through intelligent searching algorithm to further achieve better detection accuracy while maintaining optimal time complexity.

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