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Computer Graphic and Photographic Image Classification using Local Image Descriptors

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ABSTRACT

With the tremendous development of computer graphic rendering technology, photorealistic computer graphic images are difficult to differentiate from photo graphic images. In this article, a method is proposed based on discrete wavelet transform based binary statistical image features to distinguish computer graphic from photo graphic images using the support vector machine classifier. Textural descriptors extracted using binary statistical image features are different for computer graphic and photo graphic which are based on learning of natural image statistic filters. Input RGB image is first converted into grayscale and decomposed into sub-bands using Haar discrete wavelet transform and then binary statistical image features are extracted. Fuzzy entropy based feature subset selection is employed to choose relevant features. Experimental results using Columbia database show that the method achieves good detection accuracy.

Keyword : Binary statistical image feature; Image forensics; Digital image forensic; Discrete wavelet transform; Natural image; Fuzzy entropy measure; Computer graphic image; Photo graphic image

1. INTRODUCTION

Due to highly sophisticated digital imaging hardware and equally powerful computer graphic image rendering software, the computer graphic (CG) images are difficult to differentiate from photographic images (PG) by human eye. Figure 1 shows three images each of which are difficult to classify from CG and PG. Photorealistic computer graphic images can be produced using rendering softwares like 3D Studio Max, Maya, Softimage XSI and Adobe Photoshop without having any visual artifacts. Distinguishing CG image from PG image is an important research area as these images are used in criminal investigation, newspaper and magazine, TV news reporting and courtroom evidences.

Nowadays, computer graphic imagery is easy to generate using advanced rendering softwares and can be used in computerised special effects, industrial and scientific applications such as computer animation, computer aided design and in courtroom to visualise the sequence of events in a better way. For automatic image-type classification and retrieval, classification between PG and CG images are useful[3]. Although it is difficult, but still an important task to differentiate between computer graphic and photographic images. The authenticity and integrity of the image is essential in various areas. Best example is the issue of dealing with virtual child pornography[4]. To address this issue, digital image forensic is used to detect the originality of the image and to restore its trustworthiness.

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Digital image forensic is broadly categorised into (a) active forensics and (b) passive or blind forensics[5-6]. Additional information like watermark and digital signature is present

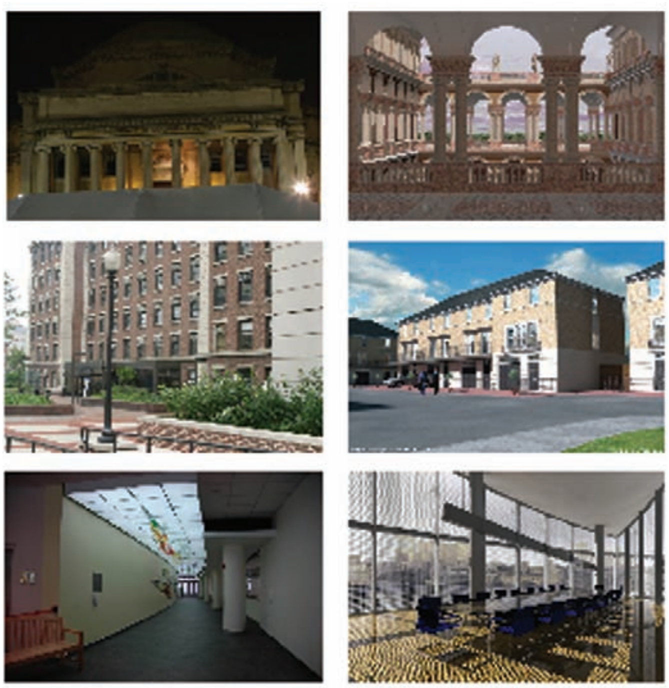

Figure 1. Examples of photographic images (first column)[1] and photorealistic computer graphic images (second column)[2].

in active forensic approach to verify the authenticity of the received image. In passive or blind forensic, the received image is used for assessing its originality without any extra information. Various methods are proposed in the literature to distinguish PG and CG images. These methodologies can be classified into two categories (a) perceptual methods and (b) statistical learning (feature based) methods. Feature based methods are further classified as (1) transform domain methods and (2) methods based on physical characteristics of the imaging equipment[7]. Perceptual methods are based on human observers to examine PRCG and photographic images[8]. In case of large number of images, this method becomes unusable. Hence, automatic computer based method is widely used to distinguish photographic images and photorealistic CG images.

1.1 Motivation and Our Work

Photographic image or natural image is any image originated from a digital imaging sensor (e.g., camera). A computer graphic or synthetic image is any scene (2D or 3D models) rendered by the software either partially or totally[9]. Based on the survey by existing approaches, there is still a major limitation such as lower detection accuracy. Our proposed work is primarily focused on enhancing the detection accuracy and finding the new features to differentiate the CG and PG images. In this paper, a method is proposed to discriminate photorealistic computer graphic and real photographic image using discrete wavelet transform (DWT) based binarised statistical image features (BSIF). Learning based binary BSIF image descriptors are different for PG and CG images and can be used to classify CG and PG images. Binary codes using BSIF are obtained for a set of natural image patches using corresponding filters with different sizes.

First, the input image is decomposed into various sub-bands with different levels using DWT. BSIF features are then extracted from approximation sub-band after second level DWT decomposition. Fuzzy entropy based feature sub-set selection algorithm is employed to select the most relevant and informative features from the input feature space. Finally, support vector machine (SVM) classifier is used to classify CG and PG images. Experimental results show that the proposed method has satisfactory detection accuracy.

2. RELATED WORK

At present, various methods are proposed for the classification of computer graphic photorealism from natural image. These methods are briefly reviewed in this section.

First-order and higher order wavelet statistical characteristics like mean, variance, skewness and kurtosis of the coefficient histograms of four wavelet sub-band and prediction error sub-band are used as features[4]. First, the input image is decomposed into three levels and from each R, G and B channel statistical features are extracted. Geometry-based features by means of the fractal geometry at the finest scale and the differential geometry at the inter-mediate scale based on textural characteristics is presented by Ng[10], *et al.* Authors found the differences between geometric object models of photographic images and computer-generated images and an average detection accuracy of 83.5 per cent was reported.

Approach based on exploiting differences of image acquisition in a digital camera and the generative algorithms used by computer generated graphics is proposed[11]. This difference is captured using the properties of the residual image (pattern noise in digital camera images) which is extracted by a wavelet transform based denoising filter. Chen[12], *et al.* introduced the statistical moments of characteristic function of the HSV image and wavelet sub-bands as the distinguishing features for detection. 234-D HSV colour model features demonstrated better performance compared to RGB model. Same authors used genetic algorithm based feature selection[13] and achieved feature dimension reduction from 234 to 100 with increased detection accuracy.

Features based on fractional lower order moments in the image wavelet domain are employed[14] resulting in an accuracy of 81.85 per cent and with a feature length of 135. Colour histogram feature, moment-based features, local patch statistics feature, features based on texture interpolation combination is used in by Sankar[15], *et al* for CG and PG classification with detection accuracy of 90 per cent. In another study, features based on the variance and kurtosis of second-order difference signals and the first four order statistics of predicting error signals are used by Li[16], *et al.* with detection accuracy of 90.2 per cent.

Conotter and Cordin[17] proposed transform domain approach in which wavelet transform domain features[4] and sophisticated pattern noise statistics feature fusion are used for classification with detection accuracy of 85.3 per cent. Hidden Markov Tree (HMT) based feature extraction approach was proposed by Pan and Huang[18] to classify the natural images and computer graphics images and obtained average detection accuracy of 84.6 per cent. Daubechie wavelet was adopted to construct the HMT in the experiment and the classification was based on SVM classifier. Zang and Wang proposed a method based on imaging features and visual features extracted from wavelet sub-bands[19]. First, the wavelet coefficients in high frequency sub-bands (different sub-images) are separated by a threshold T similar to image denoising approach. Finally, statistical characteristics and cross correlation of wavelet coefficients from sub-band components are used as features to differentiate real photographic and PRCG images.

A scheme to classify natural and fake image based on multi-resolution decomposition using 2D-DWT and higher order local autocorrelations is proposed[20]. Support vector machine (SVM) is employed for the classification, resulting in a detection accuracy of 76.82 per cent. Face asymmetry information is extracted to develop a geometric-based method to classify computer generated and natural human faces[21] using two datasets. Dataset 1 contains very realistic images, which are almost undetectable by human and Dataset 2 contains more images, related to real situations. Peng[22], *et al.* combined statistical, textural and physical characteristic features. Statistical parameters such as the mean, variance, kurtosis, skewness and median of the histograms of grayscale image in the spatial and wavelet domain are selected and the fractal dimensions of grayscale image are selected as statistical features. In addition to this, wavelet sub-bands are extracted as visual features and the mean, variance, skewness, kurtosis and fractal dimensions of the enhanced photo response non-uniformity noise (PRNU) are extracted as physical features.

Multi-resolution approach to classify CG from PG based on uniform gray-scale invariant local binary patterns (LBPs) is proposed[23]. 354-D feature vector using LBP was extracted from YCbCr colour model and then applied to support vector machines (SVM) for classification. All the above mentioned methods are summarised in Table 1. Based on the above review, we found that the classification accuracy in most the approach is still lower. Also, FV length is more in the methods, where higher detection accuracy was reported. In this article, a new local descriptor based technique is proposed with low FV dimension and good classification rate.

3. PROPOSED ALGORITHM

Computer graphic images are difficult to discriminate from photographic images by human. But their statistical properties are different. These variations in the statistical pattern are captured by BSIF features. In this section, the proposed approach for PG and CG image classification is presented using DWT based BSIF features and SVM classifier. Input image is decomposed into sub-bands using Haar DWT, and BSIF features are extracted from the approximation sub-band. Feature selection using fuzzy entropy measure is employed to choose the relevant features and remove the non important features. Finally, SVM classifier is used for differentiating PG and CG images.

As shown in Fig. 2, the proposed method consists of four main steps:

(i) *Image pre-processing :* In this step, input PG and CG

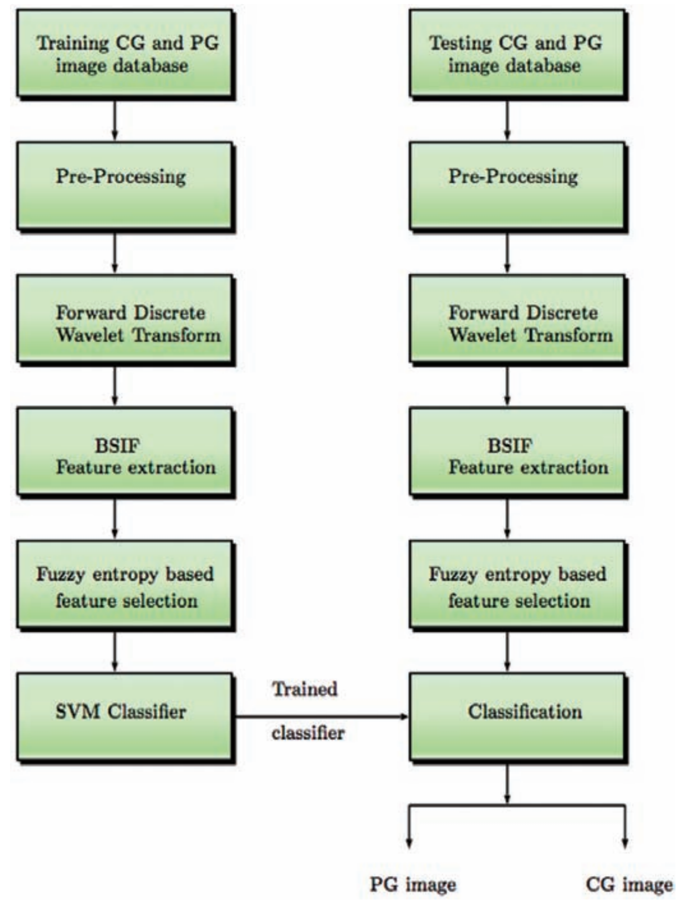

Figure 2. The framework of the proposed algorithm.

Table 1. Summary of various CG and PG classification algorithms

Algorithm (References)	Extracted features/technique	FV dimension	Classifier	Detection accuracy (%)
[4]	First and higher-order wavelet statistics and error predictors	216	SVM	82.8
[10]	Geometry-based features using the fractal geometry at the finest scale	192	SVM	83.5
[11]	Properties of the residual image extracted by a DWT based denoising filter	-	Threshold Classifier	72
[12]	Statistical moments of characteristic function of the image and wavelet coefficients	234	SVM	82.1
[13]	Statistical moments of characteristic function of the image and DWT and GA based feature selection	100	SVM	82.3
[14]	Fractional lower order moments of DWT	135	SVM	81.85
[15]	Colour histogram features, moment-based features, local patch statistics and texture interpolation features	557	Two-Class	90
[16]	Variance and kurtosis of second-order difference signals and the first four order statistics of predicting error signals	144	LDA	90.2
[17]	Similar to [4] and sophisticated pattern noise statistics	228	SVM	85.3
[18]	DWT based HMT model features	135	SVM	84.6
[19]	Statistical characteristics and cross correlation of DWT sub-bands	330	SVM	87.6
[20]	2D-DWT and higher order local autocorrelation features	225	SVM	76.82
[21]	Geometric based approach based on face asymmetry information	-	SVM	67-Dataset I 89-Dataset II
[22]	Statistical, textural and physical characteristics features	48	SVM	94.29
[23]	Uniform gray-scale invariant local binary patterns (LBPs)	354	SVM	95.1

colour images are converted into grayscale using the weighted sum of $0.2989 \times R + 0.5870 \times G + 0.1140 \times B$.

(ii) *DWT based binary statistical image feature extraction*: In the second step, grayscale image is decomposed into sub-bands using Haar DWT. Approximation sub-band is extracted and then applied to binary statistical feature extraction step resulting in *M* dimensional feature vector for each image where *M* = 256. Various parameters like statistical filter size (*N*) and bit length (*L*) and its dependence on classification accuracy are examined.

(iii) *Feature selection using fuzzy entropy measure*: To reduce the dimensionality of the feature space, fuzzy entropy measure based feature selection is used. This step involves relevant feature selection and removal of features that are not contributing to the detection process and in turn results in increasing the detection accuracy.

(iv) *CG and PG image classification using SVM classifier:* Finally SVM classifier is employed for the classification of the input image as CG and PG image. Various parameters like specificity, sensitivity and total detection accuracy (*T*) are computed in order to demonstrate the performance of the algorithm.

4. DWT BASED BSIF FEATURE EXTRACTION

The discrete wavelet transform (DWT) is a multi-resolution analysis technique which involves decomposition of an image in frequency channels of constant bandwidth using basis functions called wavelets[24]. The DWT is widely used in various signal and image processing applications due to its spatio-frequency localisation properties.

The DWT decomposes an input image into four sub-bands denoted by low-low (LL), low-high (LH), high-low (HL), and high-high (HH) at level one. LH, HL and HH (represents the high frequency components of the input image and LL contain the coarse-level coefficients. Next level of decomposition is obtained using the LL sub-band decomposition and this process is repeated to obtain the desired number of levels. Figures 3 (a) and 3(b) shows one and two level DWT decomposition. 2D-DWT can be obtained by applying 1-D DWT on the image, first in horizontal and then in vertical direction.

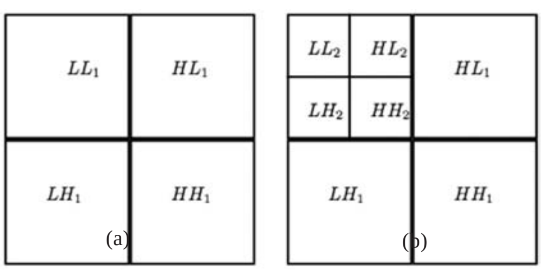

Figure 3. 2D-DWT decomposition (a) level one (b) level two.

DWT is used to analyse the CG and PG images in multi-resolution mode. HAAR wavelet is applied to the input gray image at two different levels, output of which is used for feature extraction using BSIF algorithm. DWT has been employed in order to preserve the low frequency components of the image and feature extraction is done using this low frequency band.

DWT of image $f(x,y)$ is defined as,

$$W_{\varphi}(j_0,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \Phi_{j_0,m,n}(x,y) \tag{1}$$

$$W_{\psi}^{i}(j,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \psi_{j,m,n}^{i}(x,y) \tag{2}$$

where $M \times N$ is size of the input image, $W_{\varphi}(j_0,m,n)$ represents approximation part and $W_{\psi}^{i}(j,m,n)$ defines horizontal, vertical and diagonal parts of the input image j_0 is the starting scale and $\phi_{j_0,m,n}$ and $\psi_{j,m,n}^{i}$ are the wavelet functions.

A CG and PG classification method based on local image descriptor called BSIF[25], is proposed in this paper. Earlier, BSIF features are used for hand vein pattern recognition[32].

BSIF approach is inspired by LBP and local phase quantisation (LPQ) local feature descriptors in which each pixel is represented as a binary code. The binary code is generated by computing the filter response which is trained by utilizing the statistical properties of the natural images. The filters are learned by maximising the statistical independence using Independent component analysis (ICA) from training image patches. Randomly sampled 50000 image patches from 13 different natural images are used to train each set of filters[26]. Desired optimal set of filters can be obtained by maximizing the statistical independence.

Design of natural statistic filters consists of the following steps:

(i) Conversion of input RGB images into grayscale
(ii) Mean intensity subtraction of each patch size of 32×32.
(iii) Whitening (process that makes all the variables uncorrelated and unit variance) using Principle Component Analysis (PCA)
(iv) Estimation of independent component analysis (ICA).

For a given image, $f(x,y)$ and a linear filter is represented by $h_i(x,y)$, the filter response can be computed as[33],

$$s_i = \sum_{x,y} f(u,v) * h_i(u,v) \tag{3}$$

where *i* represents the basis of the filter and *x*, *y* represents image and filter dimension. $h_i(u,v)$ is the transfer function of the filter, *u* and *v* are the radial frequencies of the filter mask computed from the image size $(u,v) = (\frac{M}{2}, \frac{N}{2})$. *M* and *N* is height and width of the image, respectively. The linear filter set *F* used in this experiment is computed by the variable size natural image patches earlier employed for deriving natural image statistics using ICA[26].

These set of filters increase the statistical independence of the filter response and the statistical property of natural image patches extracts the textural features. Also, to obtain set of filters F, ICA based technique is used and by maximizing the statistical independence filters are estimated. Detailed procedure to obtain these set of filters is explained[26].

Binary output is generated using the rule,

$$\begin{aligned} b_i &= 1; S_i = 0 \\ &= 0; otherwise \end{aligned} \tag{4}$$

where s_i is the filter response computed using Eqn (3).

From Eqn (4), the BSIF features are extracted as the pixels binary code histogram that effectively represents the textural properties in the 2D image. Figures 4 and 5 shows BSIF features extracted from the input CG and PG image respectively using 11×11 8-bit filter. Figure shows the changes in textural and smoothness characteristics of CG and PG images and effectiveness of BSIF features for classification of CG and PG images.

Filter size $N \times N$ and length of bit strings (L) are the two important parameters to evaluate the BSIF local feature descriptor for effective classification of CG and PG images. We carried out various experiments using different filter sizes $\{N \times N = 3\times3, 5\times5, 7\times7, 9\times9, 11\times11, 13\times13, 15\times15, 17\times17\}$ and with five different bit lengths $\{L = 5, 6, 7, 8, 9\}$ $\{L = 5, 6, 7, 8, 9\}$. Considering the accuracy and feature length, the filter of size 11×11 with bit length of 8 bits is selected.

Figure 6 depicts the natural image features extracted using the BSIF for various patch size and fixed bit length of 8 bits. It is evident that the extracted BSIF features varies as the patch size changes. It is also observed that an increase in patch size results in more prominent BSIF features. The basic steps of the feature extraction is shown in Algorithm 1.

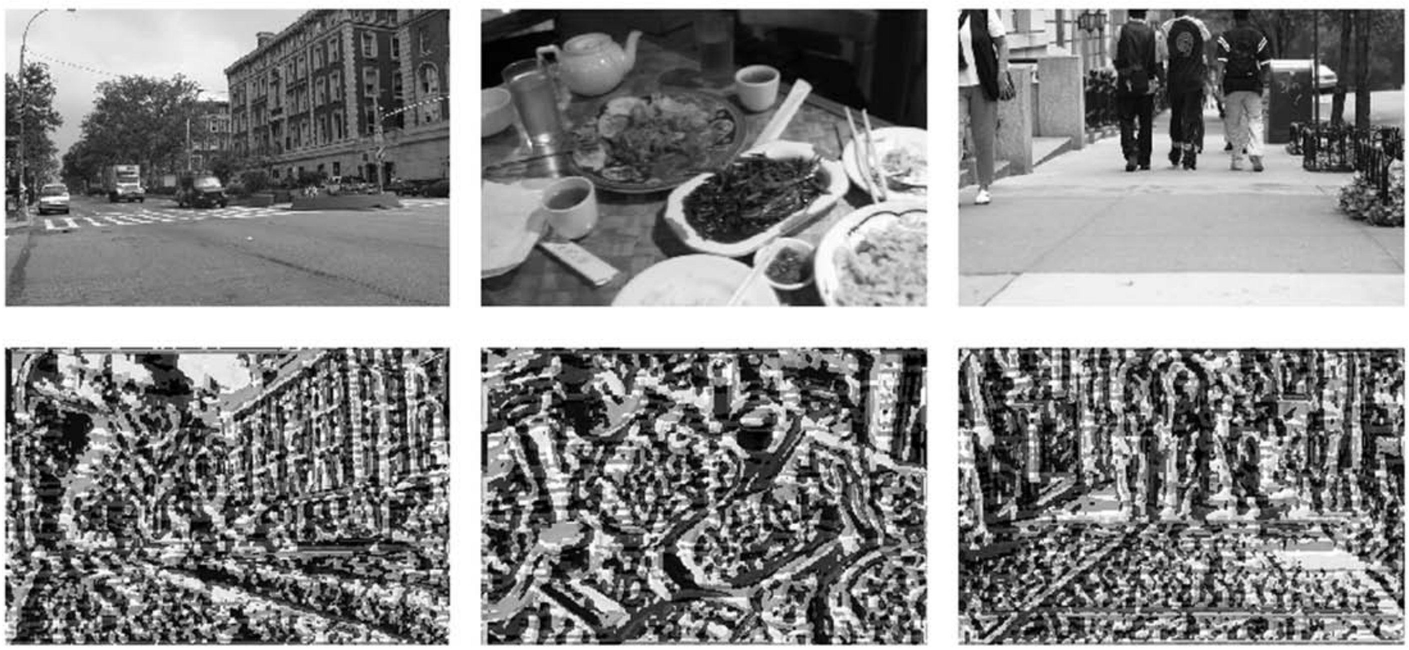

Figure 4. Examples of photographic images (first row) and corresponding BSIF features (second row) using 11x11 filter.

Figure 5. Examples of computer graphic images (first row) and corresponding BSIF features (second row) using 11x11 filter.

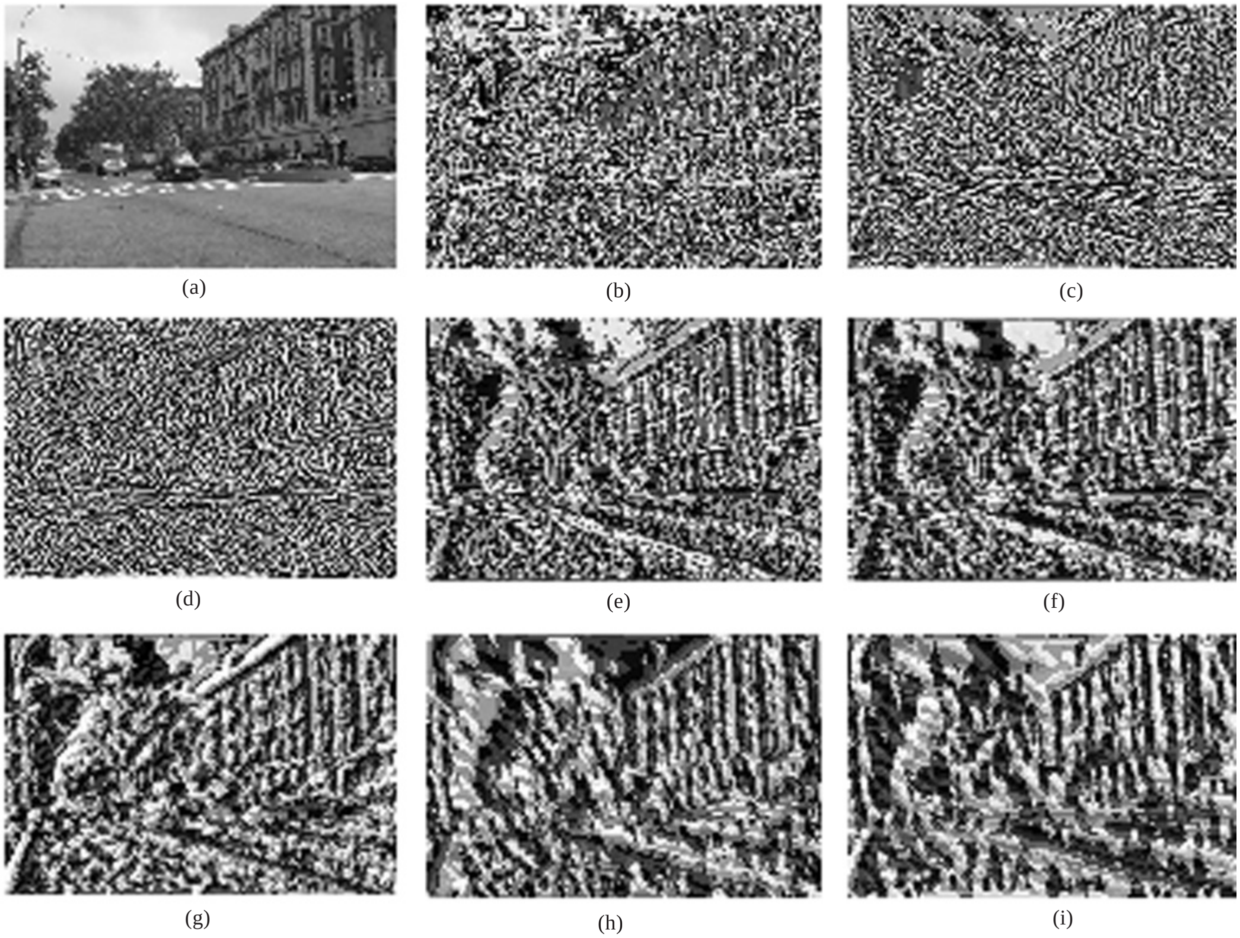

Figure 6. BSIF features extracted with various patch sizes bit length of 8 bits (a) Input photographic image (b) 3x3 (c) 5x5 (d) 7x7 (e) 9x9 (f) 11x11 (g) 13x13 (h) 15x15, and (i) 17x17.

Algorithm 1. Feature extraction algorithm

Input: Input RGB image $k, h_i(u,v)$

Output: BSIF feature vector, f

for i = 1 to **do**

Transform RGB image into grayscale

Apply 2-level Haar wavelet transform

$X \leftarrow$ approximation sub-band

$C \leftarrow X * h_i(u,v)$

$b_i \leftarrow$ compute BSIF local features using C

$f_i \leftarrow b_i$

end

5. FEATURE SELECTION USING FUZZY ENTROPY MEASURE

Feature subset selection is a technique of selecting a subset with most relevant features. Feature selection techniques are used to simplify the models and to reduce the training and testing times as it reduces the dimensionality of the data. In this work, feature selection method is employed using fuzzy entropy measure to choose the relevant features with good separability for the detection task.

Fuzzy entropy[27-28] involves fuzziness uncertainties. Using the steps given as follows, we compute fuzzy entropy of each variable (feature)[29-30].

(i) The membership of each feature M_c in all clusters is computed and normalised using FCM fuzzy c-means clustering algorithm (FCM).

(ii) The parameter match degree D_M is obtained by summation of member-ship of feature x_d in class c divided by the membership of feature x_d in all C classes.

$$D_M = \frac{\sum_{x_d \in c} M_c(x_d)}{\sum_{x_d \in C} M_c(x_d)} \tag{5}$$

(iii) For the feature from the class C, the fuzzy entropy is given by

$$F_c = -D_M \log D_M \tag{6}$$

Using Eqn (6), each feature fuzzy entropy that represents the information content is computed. Features having higher entropy values does not contribute in the PC and CG classification process (features with small information content). Feature subset generation process contains a collection of feature with small entropy value. The fuzzy entropy measure results in scoring and ranking of features. Number of features having the lowest values can be selected using a threshold T. Selecting the features based on threshold T ensures the removal of non-contributing and redundant features. Normalisation is done over all the entropy values obtained in the range [0:1] and threshold T is used to select the features. If $F_C \prec T$, the feature is selected and when $F_C \succ T$ the feature from the final subset is discarded.

Major task is to choose the optimum value of threshold *T*. We varied *T* to select the optimum value and to retain the features with smaller entropy values that are contributing to the output classes with minimum overlap. Reduction of the insignificant features has many advantages like minimising training and testing times and reducing the number of measurements required and thus enhancing the classification accuracy.

6. EXPERIMENTAL RESULTS

6.1 Experimental Setup

The proposed method described in section 3 is tested using CG and PG image databases to demonstrate the performance of the algorithm. For experiment, 800 photographic images and 800 computer generated images were used. All the images were colour images in JPEG format. The photographic image database consists of randomly selected 800 images from Columbia University Image Database[1] and 800 photorealistic computer graphic images were downloaded from[2]. Database consists of images from outdoor and in-door scenes including human faces, owners, architectures and trees with different spatial resolution.

Support vector machine (SVM) of radial basis function (RBF) kernel[21] is used as the classifier. SVM is a supervised machine-learning algorithm based on statistical learning theory and is widely used in pattern recognition applications due to its good classification performance. 70 per cent images (560 images) are randomly selected for training the classifier and the remaining 30 per cent (240) for testing.

SVM model parameters selection can improve the SVM classification accuracy. The two parameters; (1) regularization parameter *C* and (2) parameter gamma (γ) were used. Before classification, every component in the feature vector is normalised in the range [0,1] which plays a balanced role. The radial basis function (RBF) is used as kernel function and LIBSVM is utilised for the SVM implementation[31]. LIBSVM is an integrated open source machine learning libraries developed at the National Taiwan University for support vector classification, regression and distribution. By 10-fold cross validation based on leave-one-out, the RBF kernel function parameters C and γ are obtained. Figure 7 shows the parameter optimisation process. The x and y axes are the two parameters C and γ of SVM respectively and lines of different colours represent the accuracy by different contours using these two parameters during the process of cross validation. The algorithm performance is evaluated in terms of sensitivity, specificity and total detection accuracy (*T*) and computed from Eqns (7-9).

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

$$T = \frac{TN + TP}{TN + TP + FN + FP} \quad (9)$$

TP represents the CG images detected as CG, TN describes the PG images detected as PG, FP represents the PG images detected as CG and FN indicates CG images detected as PG. All the implementation is carried out using MATLAB 2013a and performed on the computer with Intel Core-i3 370 M Processor, 2.4 GHz and 2.00 GB RAM.

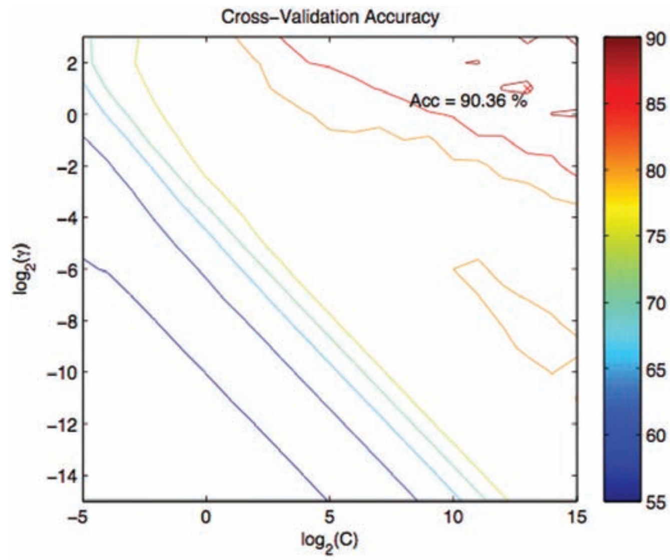

Figure 7. Parameters optimisation process.

Table 2 presents the detection rate using the proposed algorithm with feature vector length of 256-D. As seen from Table 2, the true negative detection accuracy of proposed approach is satisfactory whereas the sensitivity is lower compared to specificity. The average detection accuracy found was 87.72 per cent. Table 3 depicts the detection rate using fuzzy entropy measure based feature selection algorithm. We choose different values of threshold *T* = (0.6, 0.7, 0.8, 0.9) resulting in different feature vector length for each value of *T*. It is evident from the table that the detection rate decreases as the threshold value decreases (resulting in lower feature vector dimensionality). The detection accuracy is maximum in case of *T* = 0.9.

ICA filter size and its impact on BSIF feature extraction is described in Section 4. Figure 8 shows the plot between detection accuracy and filter size. Filter size was varied from $\{N \times N = 3\times3, 5\times5, 7\times7, 9\times9, 11\times11, 13\times13, 15\times15, 17\times17\}$ and accuracy rate was computed. It can be seen from the figure that, the detection rate is lower in case of lower patch size of the filters and it increases as patch size increases. It was

Table 2. Specificity, sensitivity and classification accuracy in (per cent)

Specificity	Sensitivity	Classification accuracy
95.84	79.59	87.72

Table 3. Effect of threshold (T) on detection rate

Threshold (T)	FV dimension	Specificity	Sensitivity	Classification accuracy
0.6	123	69.17	60.42	64.80
0.7	166	79.59	68.75	74.17
0.8	217	86.67	74.59	80.63
0.9	238	95.42	78.75	87.09

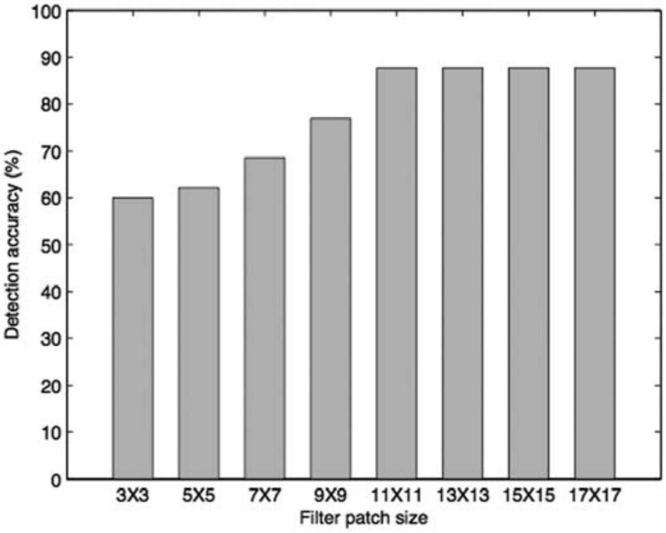

Figure 8. Natural statistic filter size and corresponding detection accuracy.

observed that detection rate remains constant beyond the patch size 11×11.

Additional experiments were carried out to demonstrate the effect of number of DWT decomposition levels on detection rate. It was observed that the increasing decomposition level was not resulting in increase of classification accuracy. Hence we choose second level DWT decomposition for feature extraction. It is important to mention here that the feature length is same for all the decomposition levels.

In order to evaluate the performance of the proposed features, we compare it with the various existing methods. The results are shown in Table 4. In Table 4, Proposed I method is having feature vector dimension of 256 without applying feature selection. Classification accuracy obtained in this case was 87.72 per cent. As discussed above, various threshold values are used to remove redundant features from the large input feature set. Proposed II method in Table 4 indicates the classification rate when threshold set to T= 0.9 and resulting in FV dimension of 238. In this case, the accuracy is slightly

Table 4. Comparison of test accuracy

Algorithm (References)	Feature size	Classifier	Accuracy
[4]	216	SVM	82.8
[10]	192	SVM	83.5
[12]	234	SVM	82.1
[13]	100	SVM	82.3
[14]	135	SVM	81.85
[15]	557	Two-Class	90
[16]	144	SVM	90.2
[17]	228	SVM	85.3
[18]	135	SVM	84.6
[19]	330	SVM	87.6
[20]	225	SVM	76.82
Proposed I	256	SVM	87.72
Proposed II	238	SVM	87.09

decreased (87.06 per cent). It can be found that the performance of the proposed scheme is better than all the methods except[15-16]. Still more research is needed on understanding and exploring new feature descriptors which can improve the performance of the classifiers and to keep the feature size minimum.

7. CONCLUSIONS

Classification of computer graphics from photographs has become an important research topic in the field of passive image authentication. Photographic image and computer graphic image classification using DWT based multi-resolution analysis and binary statistical feature is proposed in this article. Fuzzy entropy based feature selection approach is employed to extract the relevant features and SVM is used for classification. Experimental results show that the proposed method achieves good detection accuracy using the local descriptors.

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