Is It Fake or Real?

Anderson Rocha and Siome Goldenstein
Instituto de Computação
Universidade Estadual de Campinas
CEP 13084–851, Campinas, SP – Brasil
{anderson.rocha,siome}@ic.unicamp.br

Abstract

In this paper, we describe a new methodology to separate photographs *and* computer generated images . *We introduce the Progressive Randomization (PR) technique that captures the statistical properties of each one of these classes. Using only statistical descriptors of the* least significant bit *(LSB) occurrences, our method already performs as well or better than some comparable existing techniques in the literature, in a simple and unified manner.*

1. Introduction

Semantical knowledge about a scene enables more intelligent image processing. Digital cameras or computer applications can correct color and brightness automatically taking into account knowledge about the content of a picture. Proper image categorization is the first step toward this knowledge. Given an image, we want to describe what type of semantic scene it depicts. We can use the semantical knowledge about the scene for content based image retrieval algorithms, limiting the search to one or more classes such as *photographs* or *computer generated images* (CGIs).

In this paper, we describe a new methodology to separate photographs from *CGIs*. We introduce the Progressive Randomization (PR) technique to capture the statistical properties of each one of these classes. We have found that each of the analyzed classes have a distinct behavior under the PR approach which allows us to categorize them accurately.

2. Related Work

Many approaches to distinguish photographs from CGIs have been presented in the literature [2, 1, 3]. However, some of them have used the term CGIs to denote desktop or web page icons and not computer rendered images of 3-D scenes [2, 1]. In this paper, we consider only photorealistic CGIs.

3. Proposed method

Our categorization framework is a combination of statistical descriptors χ^2 and U_T, feature regions selection, and the progressive randomization stage.

3.1. Pixel perturbation

Given an input image I and a sequence of bits B, we define an LSB pixel perturbation the process of modulation of the LSBs of a randomly selected set of pixels S according to the sequence B. Suppose we want to perturbate a set of pixels using B = **1110**. The perturbation process is the modulation of the LSBs of four randomly selected pixels. For each bit $b_i \in B$, we set the LSB of pixel $p_i \in S$ to b_i.

3.2. Progressive randomization

The Progressive Randomization (PR) is a new methodology that captures statistical artifacts inserted during the perturbation process in each of the semantical image classes of our interest. We show that each of these classes have a distinct behavior under the PR approach which allows us to categorize these classes accurately.

The PR framework is a progressive LSB pixel perturbation. It receives the original image I as input, and returns n images, which only differ in the LSB from the original image. The output is a direct transformation of the input $O_i = T_i(I)$.

The T_i transformations represent possible perturbations of different percentages of the LSBs. In our experiments, we use $n = 6$ with percentages 01%, 05%, 10%, 25%, 50%, and 75%. For the original image and for each generated image, we compute the chosen statistical descriptors values in the selected regions.

We are interested in the variation rate of our descriptors rather than in their direct values, that is, $Norm(O_i) = d_j(O_i)/d_j(I)$, where d_j denotes a descriptor of an image region $1 \leq j \leq k$.

3.3. Feature regions selection

Local image properties do not show up under a global analysis. We use local regions to capture globally variations in a localized fashion. Given an image I, we want r regions with size $l \times l$ pixels that have enough information to produce good descriptors.

3.4. Statistical descriptors

Any possible LSB perturbation procedure changes the contents of a selected number of pixels. This implies in a change of pixel values statistics in a local neighborhood.

An L-bit color channel can represent 2^L possible values. If we split these values into 2^{L-1} pairs which only differs in the LSBs, we are considering all possible patterns of neighboring bits for the LSBs. Each of these pairs are called *pair of value* (PoV) in the sequence [5].

When we disturb all the available LSBs with a random binary sequence B, the distribution of odd and even values of a PoV will be the same as the 0/1 distribution of B. The arithmetical mean remains the same in each PoV and we can derive the expected frequency through the arithmetic mean between the two frequencies in each PoV.

We can apply the χ^2 (chi-squared test) [5], and U_T (Ueli Maurer Universal Test) [4] over these PoVs to detect the perturbation process.

4. Experiments and results

In this section, we show the accuracy of our approach with the selected classifier and compare our results with previous work in the literature [2, 1, 3].

We validate our methodology in a 19,500-image database with 12,000 photographs, and 7,500 CGIs. The class *photographs* includes daily-life scenes respectively of outdoors and indoors environments. The class of *CGIs* includes images that were rendered using software packages like 3D Studio Max, Maya, Blender, and Imagine. The photographs come mainly from FreePhoto[1]. The GGIs come mainly from The Internet Ray Tracing Competition (IRTC)[2] and from Raph 3D Artists[3].

4.1. Validation

We select eight spatially-constant regions. For each region, we calculate χ^2 and U_T. With $n = 6$ possible transformations, we have 112 descriptor values. After normalization, our classification procedures operate on a 96-dimensional space. We generate the 96-d feature vector of an 512×512-pixels image in 6.1 seconds on an AMD 64 bits 3,200+ with 2 GB of RAM.

1 http://www.freephoto.com
2 http://www.irtc.org
3 http://www.raph.com

4.2. Photographs vs CGIs

Lyu and Farid [3] showed that a statistical model based on first- and higher-order wavelet statistics reveals significant differences between photographs and CGIs. We compare the results reported by Lyu and Farid [3] (LF) with ours (PR) in Table 1. We perform the classification using, mostly, the same image set and 10-fold cross-validation with SVM classifier.

Approach	Photographs		Photorealistic CGs	
	μ_1	σ_1	μ_2	σ_2
LF	66.8%	–	98.8.%	–
PR	98.7%	2.7%	95.7%	5.7%

Table 1. LF vs. PR.

PR approach distinguishes *photographs* from *CGIs* with an average accuracy of $\frac{\mu_1+\mu_2}{2} = 97.2\%$ while the average accuracy of LF's approach is about 82.8%. PR approach correctly classifies 98.7% of the *photographs* which is about 32 percentile points better than LF's approach.

5. Conclusions and Future Work

We have presented a new methodology that allows us to diferentiate *photographs* from *CGIs* with an overall accuracy above 90%.

Our future work includes a theoretical analysis of the relationship among progressive randomization, and information theory. We are also interested in a multi scale analysis of our approach to take into account the advantage of spatial coherence. We also plan to apply our technique to other types of image classification problems.

References

[1] C. J. S. O. et al. Classifying images collected on the WWW. In *XV SIBGRAPI*, pages 327–335. IEEE, 2002.

[2] V. A. et al. Distinguishing photographs and graphics on the WWW. In *CBAIVL*, pages 10–17. IEEE, 1997.

[3] S. Lyu and H. Farid. How realistic is photorealistic? *IEEE Transactions on Signal Processing*, 53:845–850, Feb 2005.

[4] U. Maurer. A universal statistical test for random bit generators. *Journal of Cryptology*, 5:89–105, Feb 1992.

[5] A. Westfeld and A. Pfi tzmann. Attacks on steganographic systems. In *3^{rd} Intl. IH Workshop*, pages 61–76. Springer, 1999.

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