A Novel System for Detecting Adult Images on the Internet

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Abstract

As Internet usage has increased, the risk of adolescents being exposed to adult content and harmful information on the Internet has also risen. To help prevent adolescents accessing this content, a novel detection method for adult images is proposed. The proposed method involves three steps. First, the Image Of Interest (IOI) is extracted from the image background. Second, the IOI is distinguished from the segmented image using a novel weighting mask, and it is determined to be acceptable or unacceptable. Finally, the features (color and texture) of the IOI or original image are compared to a critical value; if they exceed that value then the image is deemed to be an adult image. A Receiver Operating Characteristic (ROC) curve analysis was performed to define this optimal critical value. And, the textural features are identified using a gray level co-occurrence matrix. The proposed method increased the precision level of detection by applying a novel weighting mask and a receiver operating characteristic curve. To demonstrate the effectiveness of the proposed method, 2850 adult and non-adult images were used for experimentation.

Keywords: K-means, adult images, image features, weighting mask, receiver operating characteristic curve, internet

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1. Introduction

According to the International Telecommunication Union [1], the worldwide Internet population has reached about 1.5 billion. The large number of adolescents connected to the Internet means they have ever more opportunities to access inappropriate content, such as adult images. In many cases, these images are easily accessible to adolescents and some even target them. Thus, it is important to implement measures that help prevent adolescents from accessing this type of content, so this subject area has come to the attention of researchers.

A variety of approaches are used to filter out adult image content. These can be classified into three categories: IP-based blocking of adult images, filtering based on textual content, and filtering based on visual content. However, there are potential problems with each method, including inefficiency, impracticality, and the phenomenon of over-blocking. In an effort to improve efficiency, many researchers have investigated filtering based on visual content as a means of identifying image content. In particular, many researchers have developed image-based detection methods. Jau-Ling et al. [2] used the MPEG-7's color descriptor, texture descriptor, and the proposed compactness descriptor in order to better identify adult images. Jinfeng et al. [3] used techniques that endeavored to describe the typical characteristics of the human torso. Hu et al. [4] proposed a method of recognition that was based on a combination of the textual context and the image itself. Hammami et al. [5] developed Web-Guard, a web filtering engine that combines analyses of textual, structural and visual content. It is clear from the work of these and other scholars that if an identification process is to function efficiently and be effective, adult image content must be identified on the basis of Content-Based Image Retrieval (CBIR). In CBIR, the primary emphasis is on identification and automatic extraction of computable visual features such as color, texture and shape [6][7].

The detection of adult images is typically regarded as an image classification problem. In general, the first stage of classifying skin-like regions involves identifying the color and textural information. Information extracted from skin-like regions, including color, texture and shape features, is then analyzed to distinguish between adult and non-adult images. Studies have shown that detection based on color is a more accurate detection method than one based on texture or shape. Smith et al. [8][9] created a method that used color as the identification criterion and included color indexing using histogram intersection. Most kinds of images include unique textural features. For example, images of textiles, grass and fur can easily be categorized on the basis of texture. Hermes et al. [9][10][11] used a co-occurrence matrix for image retrieval systems in order to determine textual features. Recently, Xuanjing Shen et al. [12][13] used an adult image detection method based on specific parts. A problem with this method is that it is difficult to detect adult images if the specific parts are not present. There are countless types of adult images. This paper proposes a detection system for general adult images.

The remainder of the paper is organized as follows; Section 2 provides an overview of the method that we developed to help distinguish between adult and non-adult images. Section 3 outlines the preprocessing method for the IOI extraction, which employs the K-means algorithm and the weighting mask. The IOI is then identified from the segmented image and judged either acceptable or unacceptable. An acceptable IOI and the color quantization of the original image are analyzed using critical values for adult image features (color and texture), and each image is identified as either an adult or a non-adult image. Section 4 presents the experimental results demonstrating the effectiveness of the proposed method. Finally, section 5 provides our conclusions.

2. Overview of the Method

A flow chart of the proposed system is shown in **Fig. 1**. First, the K-means algorithm is applied to the original image in order to divide it into three sections, and the weighting mask is used to obtain the IOI. The three images are then converted to binary images in order to ensure they are compatible with the weighting mask. The weighting mask is then applied to the binary images and the image with the largest weighting mask value is assigned as the main IOI.

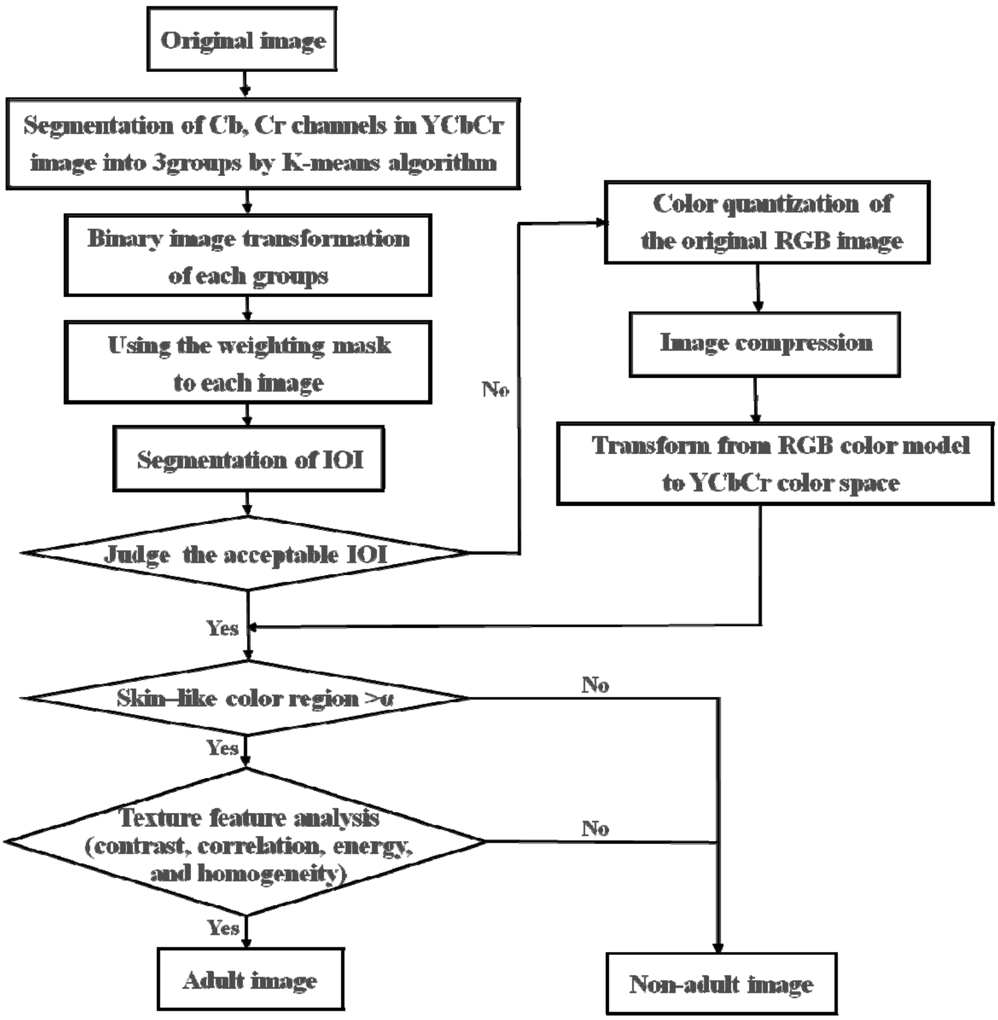


Fig. 1. Method for the detection of adult image content

Second, by comparing the size of the original image with that of the IOI, the system can decide whether an image is acceptable. Finally, a receiver operating characteristic curve analysis was performed to identify the optimal critical value (α) representing the number of skin-like pixels an image would need in order to be classified as an adult image. That is, any images that have more skin-like pixels than the number implied by the critical value are identified as adult images, and any images that have less skin-like pixels than the critical value are identified as non-adult images. At this point, an adult image is identified by the ratio of the area of the skin-like region to the area of the IOI. The textural features of the first identified adult image (otherwise known as the IOI) are then analyzed to determine whether a second adult image can be detected. A gray level co-occurrence matrix is used for this textural feature analysis. If the analysis of the extracted textural features reveals that the IOI has a region featuring skin-like pixels, the extracted IOI is regarded as being part of an adult image; otherwise, it is regarded as being part of a non-adult image. If the selected IOI is deemed unacceptable, the skin-like color and textural features are analyzed for the color quantized original image. In this case, an original RGB (red, green, blue) image is quantized, and compressed. The quantized RGB image is converted to the YCbCr color space, and the system then analyzes the converted image's color and texture. The benefit of this scheme is that it reduces the calculation time without losing the information in the original images.

3. Proposed Detection of Adult Image Content

3.1 Segmentation of the IOI

To obtain the IOI, the color image is first split into segments in order to distinguish the IOI from its context. The proposed method does not use an algorithm to segment the image, but instead detects objects within it.

Mojsilovic et al. [14] found that people tend to view images in terms of three or four major colors. Bearing this in mind, our system uses the K-means algorithm to obtain information regarding the adult image content, which is used to segment content into three groups.

The segmented groups are then converted to binary images so that the weighting mask can be employed. The proposed weighting mask is shown in Fig. 2; 250 adult images were scrutinized and the main object was identified according to its location and the nature of the pixels.

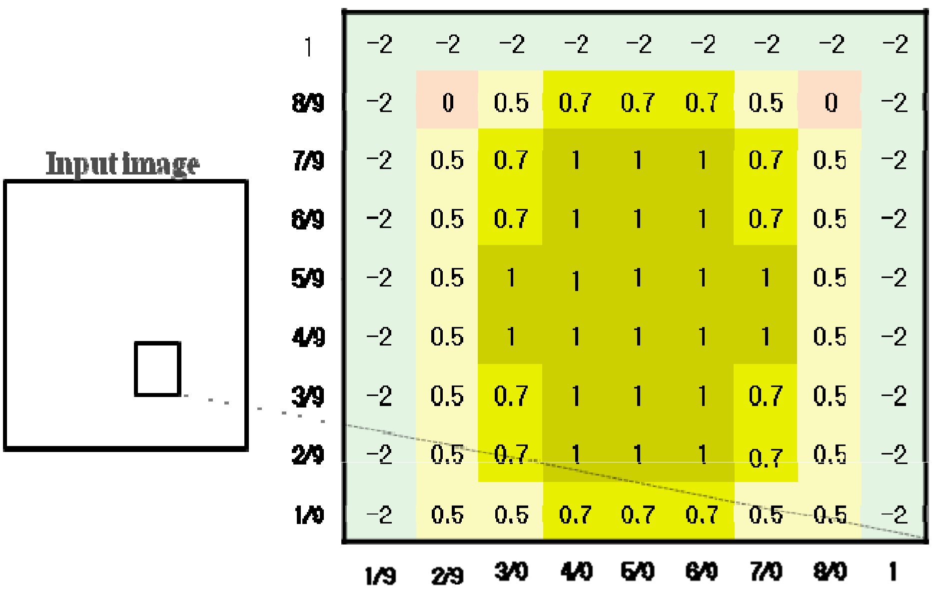
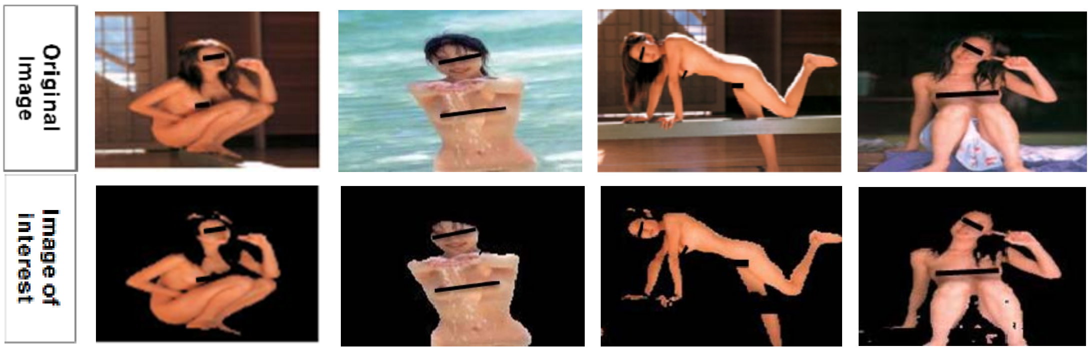


Fig. 2. Weighting mask

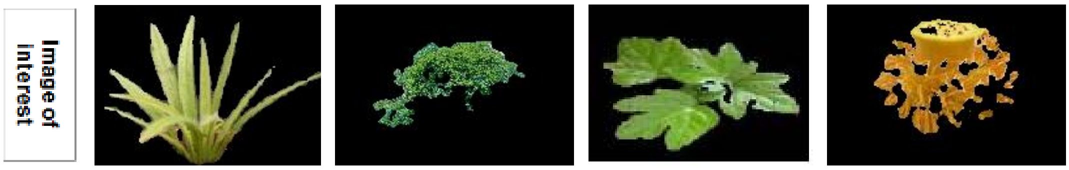
In accordance with the method used by Kang [15], the object is extracted using a weighting mask; the width and height of the color image are denoted *m* and *n*, respectively. As Ha's research has indicated [16], the positions of the objects do not lie where the artificial vertical and horizontal lines dividing the image into nine equal parts (m/9, n/9) intersect. Instead, adult images on mobile phones or adult websites typically take up a large proportion of the image and depict a naked body near the center. We found that objects are rarely found around the edges of an image. We extracted IOIs from 250 sample adult images taken by professional photographers, and overlapped each object associated with a value of 1. To obtain the mask, we added the values of all objects and divided the total by 250. Positive weights (1, 0.7, 0.5, 0) were assigned to the pixels, therefore, negative weights (-2) were assigned to these regions. Segmented images were obtained from the binary images using a critical value of 0.09. The weighting mask was then applied to each region and the image that had the largest end value was selected as the IOI. We defined an IOI as being unacceptable in two cases: (1) when the IOI detected in the image is small and not the main object or (2) when the system fails to identify even the largest IOI from the image as an independent object.

If the segmentation does not yield an acceptable IOI (i.e., where the IOI is relatively small or difficult to define, or where the image cannot be evaluated using the weighting mask), we use the color quantization of the original image to analyze the color and textural features of the image. **Fig. 3** shows the results of IOI extraction.



(a)

(b)

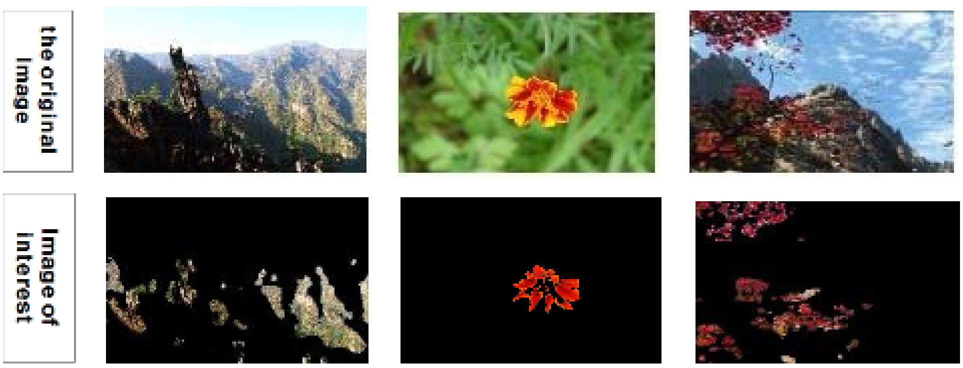


(c)

(d)

Fig. 3. Results of IOI extraction: **(a)** adult image, **(b)** animal, **(c)** plant, **(d)** landscape

In some images, the main objects are too small to allow the image to be evaluated using the weighting mask. In these cases, the extracted IOI cannot be deemed acceptable. For example, landscape images generally do not include a main object. In this case, we attempted to extract skin-like color features from the original images. **Fig. 4** shows unacceptable IOIs extracted from the original images.

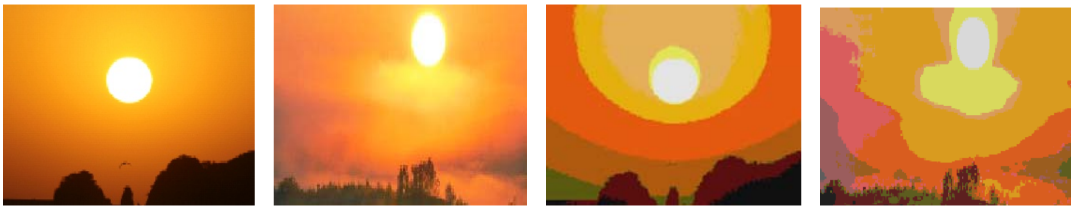


(a) (b) (c)

Fig. 4. Results of unacceptable IOI extraction: **(a)** landscape, **(b)** small object in image, **(c)** image evaluated incorrectly by the weighting mask

3.2 Color Quantization of the Original Image

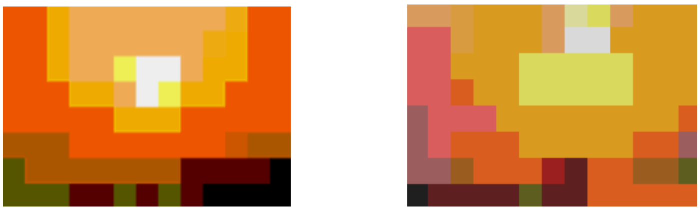
For the original images **(a)** and **(b)** of size $m \times n$ (192 × 128) shown in **Fig. 5**, three channels (red, green, and blue) were extracted. In each channel, pixels with brightness intensities between 0 and 255 were quantized into four bin values. As a result, the quantized images are represented with 64 (4 × 4 × 4) color values, as shown in images **(c)** and **(d)** of **Fig. 5**.



(a) (b) (c) (d)

Fig. 5. Color image quantization: original images (**(a)** and **(b)**) and quantized images (**(c)** and **(d)**)

The values of the pixels in the area surrounding a certain point (pixel) remain similar after quantization, and the entire image can be compressed without any significant loss of information [17]; this means that the time needed to calculate the statistical information characterizing the image's color and texture is significantly reduced. **Fig. 6** presents the compression of images (c) and (d) in **Fig. 5**, which have been reduced to 1/15 - i.e., ($m \times n$)/15.



(e) (f)

Fig. 6. Compressed images after color quantization

RGB images have three-dimensional structures and their similarity is determined by the number of matching pixels at the same points. Thus, as shown in **Fig. 7**, the images were converted to one-dimensional structures and the number of matching pixels at the same points (P(1), P(3), P(6)) was calculated. The total number of matching pixels at the same points is then normalized [0, 1] by equation (1).

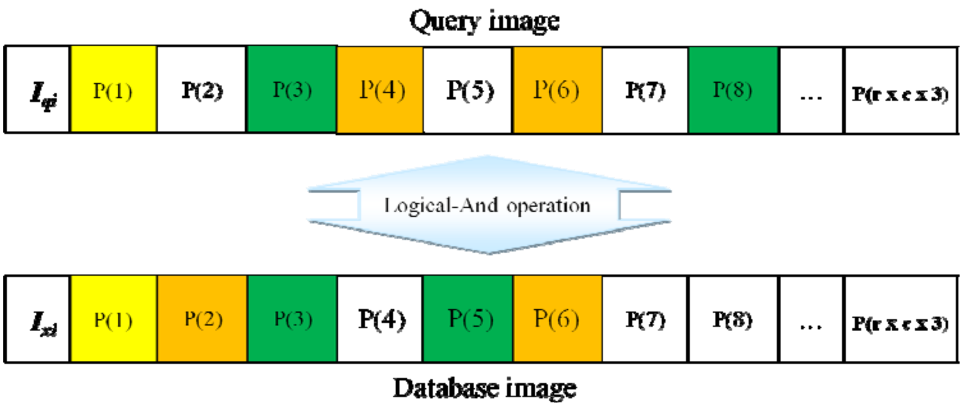


Fig. 7. Comparison of similarity after converting images to one-dimensional structures

$$Cnt = \sum Count(I_i(q), I_i(x)), \quad \text{if } |I_i(q) - I_i(x)| = 0.$$

$$d_{Quant}(T(q),T(x))=\frac{Cnt}{r\times c\times 3} \tag{1}$$

Where $i = 1,2,\ldots,r \times c \times 3$, $I_i(q)$ is the one-dimensional expression of the compressed query RGB image, and $I_i(x)$ is the one-dimensional expression of the compressed database image. Furthermore, $Count(I_i(q), I_i(x))$ is the number of matching pixels between the query image and the compared image, $T(q)$ is the query image, $T(x)$ is the database image, and equation (1) signifies that the similarity between the images is equalized between [0, 1]. In this case, the similarities between the database images (Figures (a, c, e)) and the query image (Figures (b, d, f)) are shown in **Table 1**.

Table 1. One-to-one similarities between database images and query images

Images	Fig. 5(a, b)	Fig. 5(c, d)	Fig. 6.(e, f)
Similarity	0.0027	0.4215	0.4327

After all, for determining the similarity of **Fig. 5** (a, b) images, it is more reasonable to compare the quantized images in **Fig. 5** (c, d) than to compare the original images. Moreover, comparing the images in **Fig. 6** (e, f) can maintain the characteristics of the original images, complement the loss of position information, which is a shortcoming of histograms, and reduce the calculation volume to 1/15.

3.3 Skin-Like Color Feature Extraction

The next stage in the process involves analyzing either the skin-like color features in the case of acceptable IOIs or the color quantization in the case of original images from which an acceptable IOI cannot be extracted. In case where the IOI pixels have a unique value and the rest of the IOI region has a zero value, the nature of the IOI pixels is determined and the number of skin-like pixels is assessed. However, it is also necessary for the system to analyze the color features of the color quantization of original images with unacceptable IOIs. If the number of skin-like pixels exceeds the critical value then the system identifies the image as an adult image. The proportion of the original image taken up by the skin-like region is also considered; if this region exceeds the critical value for the entire IOI, the system identifies the original image as the first adult image.

Wang and Chang [18] conducted a skin color analysis directly in the chrominance plane (Cb, Cr); however the reliability of their results is in doubt because many incorrect images were identified as adult ones, owing to the fact that many image regions often had a similar color to skin color or a natural background. Garcia and Tziritas [19] showed that skin-like pixels had a stronger correlation with the Cb and Cr components than with the Y component. A pixel is considered to be skin-like if its Cb and Cr components meet the following restrictions:

if Y > 128, $\theta_1 = -2 + (256 - Y)/16$; $\theta_2 = 20 - (256 - Y)/16$;
$\theta_3 = 6$; $\theta_4 = -8$

if Y≤128, $\theta_1 = 6$; $\theta_2 = 12$;
$\theta_3 = 2 + Y/32$; $\theta_4 = -16 + Y/16$

$C_r \geq -2(C_b + 24)$; $C_r \geq -(C_b + 17)$;
$C_r \geq -4(C_b + 32)$; $C_r \geq 2.5(C_b + \theta_1)$;

$$C_r \geq \theta_3; \qquad C_r \geq 0.5(\theta_4 - C_b);$$
$$C_r \leq (220 - C_b)/6; \qquad C_r \leq 4(\theta_2 - C_b)/3.$$

These equations can be used to accurately determine whether a pixel is skin-like; indeed they take into account a variety of skin features, including apparent skin color differences depending on lighting conditions and skin color differences between people from different ethnicities.

3.4 Textural Feature Analysis

The textural feature distributions can also be used to discriminate between adult and non-adult images. This is because most non-adult images have sharper edges than adult images, which usually have smooth textural features. This paper uses a gray level co-occurrence matrix to extract the textural features [20]. In order to conduct a statistical analysis of the textural features of an image, the first adult image is preprocessed to a gray-level image so that a gray level co-occurrence can be applied. Of the many textural features that could be obtained from the gray level co-occurrence matrix, this paper analyzes four: contrast, correlation, energy and homogeneity.

In applied research on texture images, many case studies have shown that additional use of a texture image during image classification can help provide a qualitative classification; it may also improve the accuracy of the quantitative classification [21][22][23]. Despite this, there is still a lack of hard evidence regarding the most useful selection criteria for identifying the textural properties of an image or for comparing varying texture properties. Our research is the first time four types of texture properties have been used to detect adult image content.

Skin-like color features are extracted from each pixel in the image and then the textural features are extracted from each block in the image. We transformed the block-level textural attributes into a pixel-level textural attribute by assigning the textural feature of a block to all of the pixels within the block. Where the first adult image is evaluated as a coarse region, it is regarded as a non-adult image. In all other cases, the image is regarded as an adult image.

4. Experiment and Analysis

The images used in the experiment had dimensions of 192 × 128 pixels. The function of the proposed method was verified by Matlab R2006b software in a Pentium personal computer environment, and approximately 2850 experimental images were used, including adult images, animal images (e.g., mammals, reptiles, birds and insects), landscape images (e.g., sunrise, sunset, general landscape and travel), and plant images (e.g., trees, flowers and grass); these were selected from the Internet (**Fig. 8**).

To validate the proposed method, two experiments were carried out. In the first experiment, an acceptable IOI was extracted from an original image. To verify the accuracy of the system, we determined the pixels for the IOI extracted from the original image; then, if the analysis of color features indicated an adult image, the texture was analyzed using a gray level co-occurrence matrix. In the second experiment, we determined the nature of the pixels in the color quantization of the original images extracted from an unacceptable IOI.

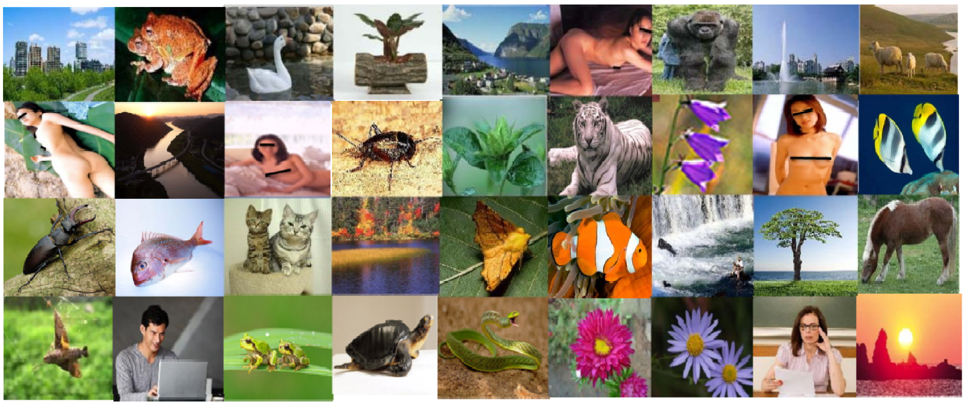


Fig. 8. Example images for experiments

4.1 Segmentation of the IOI

To determine the effectiveness of the segmentation process, 1650 categorized images selected from the Internet were used as experimental images. First, we divided the images into those that had acceptable IOIs and those that had unacceptable IOIs. We performed experiments to determine how images relevant to queries were detected. The concept of relevance is based on the detection results obtained manually by human subjects. Detection effectiveness can be defined in terms of precision rates, where the precision rate is defined as the percentage of detected images relevant to the query.

The process used a critical value of 0.4. The critical value is the ratio of the area of the IOI region to the area of the original images. **Table 2** lists the average values obtained for the IOI region in the original images.

$$\text{Average for the IOI region} = \frac{\sum_{i=1}^{n} R_i}{N} \tag{2}$$

The results obtained using Equation (2), are given in **Table 2**; N is the number of categorized queries, R_i is the IOI region, and n is the number of images. Using the above equation, we find that the average value for the landscape images is lower than that for the other images. Generally, landscape images can be recognized by the fact that they do not include a main image or if they do, the edge of the main image is indefinite [16]. Therefore, it is difficult for the weighting mask to evaluate these kinds of images.

Table 2. Average rate for IOI region from original images

Categorized Queries	Number of Images	Number of Acceptable IOIs	Number of Unacceptable IOIs	Average Rate for the IOI Region
Landscape Images	300	228	72	0.45
Animal Images	300	279	21	0.71
Plant Images	300	270	30	0.63
Adult Images	750	696	54	0.55
Total	1650	1473	177	0.585

4.2 Skin-Like Color Feature Analysis

In the first stage of the skin-like color feature analysis, the skin-like color features of acceptable IOIs were analyzed in the case of 1473 images. We computed the total number of skin-like pixels in an acceptable IOI; this detection was performed using a critical value. The critical value refers to the ratio of the area of the skin-like color region to the area of the IOI. To identify the optimal critical value, we performed a Receiver Operating Characteristic (ROC) curve analysis. The receiver operating characteristic curve analysis shows that the precision peaked when the critical value was 0.8, as can be seen in **Fig. 9**.

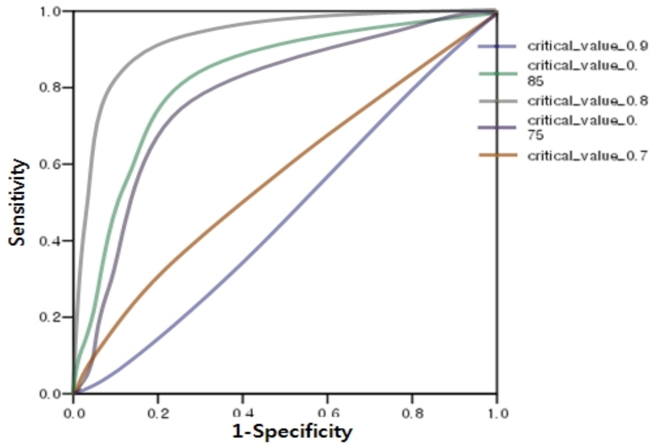


Fig. 9. The receiver operating characteristic curve

4.3 Textural Features Analysis

The textural features of 250 adult images were analyzed. The textural feature analysis used a gray level co-occurrence matrix and four textural features: contrast, correlation, energy, and homogeneity. **Fig. 10** shows the results of this analysis of the textural features for each adult image. The correlation feature has a stable value of 0.92 - 0.95.

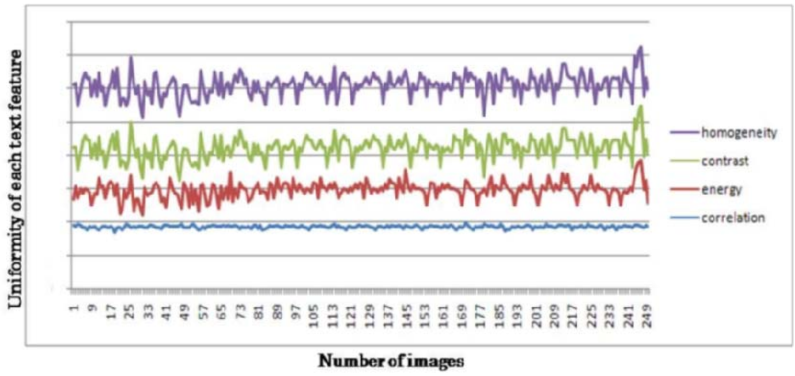


Fig. 10. Results of the textural feature analysis of adult images

The other textural features have non-uniform values. To obtain good detection performance, the weights for each feature are carefully considered; for example, we considered whether the correlation feature should be more heavily weighted then other features. In the experiment, similar weights were given to contrast, energy and homogeneity, which guaranteed good detection performance. However, correlation was a more important factor than the other features, so a weight of 0.5 was assigned to the correlation of textural information and weights of 0.17 were assigned to contrast, energy and homogeneity. The test was conducted using various weights (e.g., 0.4/0.2 and 0.6/0.3), and 0.5/0.17 had the best detection performance.

4.4 Effectiveness of Detection Method

We evaluated the effectiveness of the method by analyzing 1200 images consisting of 600 adult images and 600 non-adult images. Image data were downloaded from the Internet. The non-adult images cover three categories: animals, plants and landscapes.

Table 3. Detection results for IOIs

	Acceptable IOIs	Unacceptable IOIs	Total
Detection Rate for the IOIs	87% (1044) (number of adult images: 564, number of non-adult images: 480)	13% (156) (number of adult images: 36, number of non-adult images: 120)	100%

Table 3 shows the detection rates for acceptable and unacceptable IOIs for the 1200 images. The detection rate for acceptable IOIs is relatively high (87%, 1044 images) whereas the detection rate for unacceptable IOIs is low (13%, 156 images).

Table 4 indicates that in the acceptable IOI category, the rate of images identified as final adult images is 92.7% (556 images), and in the unacceptable IOI category, the rate of detected final adult images is 3.7% (22 images). As shown in **Table 4**, the proposed method detects 578 of the 600 adult images, indicating a reliability of up to 96.4%. Throughout the various phases of the analysis, very few non-adult images were misidentified as adult images.

Table 4. Detection results for final adult images

	Acceptable IOIs	Unacceptable IOIs	Total
Detection Rate	Adult Images 92.7% (number of detected adult images: 556)	Adult Images 3.7% (number of detected adult images: 22)	96.4%
	Non-Adult Images 77% (number of detected non-adult images: 462)	Non-Adult Images 17.3% (number of detected non-adult images: 104)	94.3%

Finally, **Fig. 11** compares the results of the proposed method with those of other methods. In other methodologies, experiments were conducted using standard data acquired by randomly selecting 500 samples (250 adult images and 250 non-adult images) from the 2850 data points of this paper. It is clear that the proposed method has the best performance.

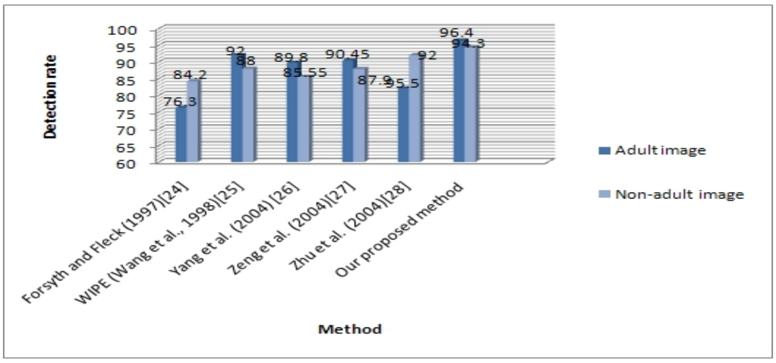


Fig. 11. Comparison of detection rates for different methods

5. Conclusions

In this paper, we have outlined a novel method for detecting adult image content. The proposed method does not use an algorithm to segment the images; instead, it focuses on identifying the color and texture of particular objects within an image. In the first stage, the K-means algorithm is used to extract the IOI from the original image. Second, the IOI is distinguished from the segmented image. Then a novel weighting mask was applied to the IOIs in order to judge whether they were acceptable or unacceptable by estimating the objects in reverse order. Finally, by separating each acceptable IOI and conducting color quantization of the original image, we determined the proportion of the image that consisted of a skin-like region, and we applied the critical value to identify the type of image. If the IOI was deemed acceptable and the color quantization of the original image exceeded the critical value, the image is regarded as the first adult image. The original image is quantized and compressed, thus reducing the calculation time without significant information loss. A receiver operating characteristic curve analysis was performed to define the optimal critical value. In our method, this process defines segmentation of the images according to areas of skin-like color, and this segmentation uses Cb and Cr in YCbCr coordinates. The final adult image is then identified according to the textural features retrieved by the gray level co-occurrence matrix. In particular, it should be noted that this kind of method, which detects human characteristics based on four texture properties, might well prove to be a useful reference in future research. Experimental results have demonstrated the effectiveness of the proposed method; indeed, it is clear that the proposed algorithm solves the problems of inefficiency and impracticality often associated with previous methods. However, it must also be noted that the proposed method was applied only to images that had relatively clear IOIs. Hereafter, we aim to devise a variety of weighting masks that will detect images with unclear IOIs.

References

[1] http://itu.int/, 2010.

[2] Shih J. L., Lee C. H. and Yang C. S., "The Adult Image Identification System Employing Image Retrieval Technique," *Pattern Recognition Letters*, vol. 28, no. 16, pp. 2367-2374, 2007.

[3] Jinfeng Yang J., Fu Z., Tan T. and Hu W., "A Novel Approach to Detecting Adult Images," in *Proc. of the 17th International Conf. on Pattern Recognition*, vol. 4, pp. 479-482, 2004.

[4] Hu W., Wu O., Chen Z., Fu Z. and Maybank S., "Recognition Of Pornographic Web Pages By Classifying Texts And Images," *IEEE Transactions on Pattern Analysis Machine Intelligence*, vol. 29, no. 6, pp. 1019-1034, June 2007.

[5] Hammami M., Chahir Y. and Chen L., "WebGuard: A Web Filtering Engine Combining Textual, Structural, and Visual Content-Based Analysis," *IEEE Transactions on Knowledge and Data Engineering*, vol. 18, no. 2, pp. 272-284, 2006.

[6] Yong R., Thomas S. Huang and Chang S. F., "Image Retrieval: Current Techniques, Promising Directions, and Open Issues," *Journal of Visual Communication and Image Representation*, vol. 10, no. 1, pp. 39-62, Mar. 1999.

[7] Imran Shafiq Ahmad, "Text-based Image Indexing and Retrieval using Formal Concept Analysis," *KSII Transactions on Internet and Information Systems*, vol. 2, no. 3, pp. 150-170, June 2008.

[8] Smith J. R. and Chang S. F., "Tools and Techniques for Color Image Retrieval," in *Proc. of SPIE, Storage and Retrieval for Image and Video Databases IV*, vol. 2670, pp. 426-437, Mar. 1996.

[9] Rui Y., Huang T. S. and Mehrotra S., "Relevance Feedback Techniques in Interactive Content-Based Image Retrieval," *in Process of SPIE, Storage and Retrieval for Image and Video Databases VI*, vol. 3312, pp.25-36, Dec. 1997.

[10] Hermes T., Klauck C., Krey J. W. and Zhang J., “Image Retrieval For Information Systems,” in *Proc. of SPIE, Storage and Retrieval for Image and Video Databases III*, vol. 2420, pp. 394-405, March 1995.
[11] Sakamoto H., Suzuki H. and Uemori A., “Flexible montage retrieval for image data,” in *Proc. of SPIE, Storage and Retrieval for Image and Video Databases II*, vol. 2185, pp. 25-33, 1994.
[12] Xuanjing S., Wei W. and Qingji Q., "The filtering of internet Images Based on Detecting Erotogenic-part," in *Proc. of 3rd International Conf. on Natural Computation, ICNC 2007*, pp.732-736, Aug. 2007.
[13] Yue W., Jun L., HeeLin W. and ZuJun H., "Automatic Nipple Detection Using Shape and Statistical Skin Color Information," *Lecture Notes in Computer Science*, vol. 5916, pp. 644-649, 2010.
[14] Mojsilovic' A., Kova'cevic' J., Hu J., Safranek R. J. and Ganapathy S. K., “Matching and Retrieval Based on the Vocabulary and Grammar of Color Patterns,” *IEEE Transactions on Image Processing*, vol. 9, no. 1, pp. 38-54, Jan. 2000.
[15] Kang S. D., Park S. S., Yoo H. W., Shin Y. G. and Jang D. S., “Development of expert system for extraction of the objects of interest,” *Expert Systems with Applications*, vol. 36, no. 3, pp. 7210-7218, Apr. 2009.
[16] Ha Y. C., “Nature Picture and Human,” *Donga Press*, Seoul, Korea, 2002.
[17] Yoo H. W, Jung S. H., Jang D. S. and Na. Y. K., “Extraction of Major Object Feature Using VQ Clustering for Content-Based Image Retrieval,” *Pattern Recognition*, vol. 35, no. 5, pp. 1115-1126, May 2002.
[18] Wang H. and Chang S. F., “A highly efficient system for automatic face region detection in MPEG video,” *IEEE Transactions on Circuits and System for Video Technology*, vol. 7, no. 4, pp. 615-628, Aug. 1997.
[19] Garcia C. and Tziritas G., “Face detection using quantized skin color regions merging and wavelet packet analysis,” *IEEE Transactions on Multimedia*, vol. 1, no. 3, pp. 264-277, Sept. 1999.
[20] Robert M. Haralick, K. Shanmugam and I. Dinstein, “Textural Features for Image Classification,” *IEEE Transactions on Systems, man and Cybernetics*, vol. 3, no. 6, pp. 610-621, Nov. 1973.
[21] Weszka J. S., Dyer C. R. and Rosenfeld A., “A comparative study of texture measures for terrain classification,” *IEEE Transactions on Systems, man and Cybernetics*, vol. 6, pp. 269-285, 1979.
[22] Zhang Y., “Optimisation of building detection in satellite images by combining multispectral classification and Texture filtering,” *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 54, no. 1, pp. 50-60, Feb. 1999.
[23] Franklin S. E., Wulder M. A. and Gerylo G. R., “Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia,” *International Journal of Remote Sensing*, vol. 22, no. 13, pp. 2627-2632, 2001.
[24] Forsyth D. A. and Fleck M. M., “Body plans,” *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 678-683, 1997.
[25] Wang J. Z., Li J., Wiederhold G. and Firschein O., “System for screening objectionable images,” *Computer Communications*, vol. 21, no. 15, pp. 1355-1360, Oct. 1998.
[26] Yang J., Fu Z., Tan T. and Hu W., “A novel approach to detecting adult images,” in *Proc. of the 17th International Conf. on Pattern Recognition*, vol. 4, pp. 479-482, Aug. 2004.
[27] Zeng W., Gao W., Zhang T. and Liu Y., “Image Guarder: An Intelligent Detector for Adult,” in *Proc. of Asian Conf. on Computer Vision*, Jeju Island, South Korea, pp. 198-203, Jan. 2004.
[28] Zhu Q., Wu C. T., Cheng K. T. and Wu Y. L., “An Adaptive Skin Model and Its Application to Objectionable Image Filtering,” in *Proc. of the 12th annual ACM International Conf. on Multimedia*, New York, USA, pp. 56-63, 2004.

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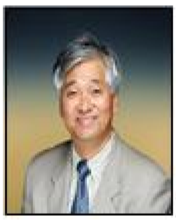

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