A Web Pornography Patrol System Based on Hierarchical Image Filtering Techniques

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Abstract

Due to the flood of pornographic web sites on the internet, content-based web filtering has become an important technique to detect and filter inappropriate information on the web. This is because pornographic web sites contain many sexually oriented texts, images, and other information that can be helpful to filter them. In this paper, we build and examine a system to filter web pornography based on image content. Our system consists of three main processes: (i) normalized R/G ratio, (ii) histogram, and (iii) human composition matrix (HCM) based on skin detection. The first process is using the pixel ratios (red and green color channels) for image filtering. The second process, histogram analysis, is to estimate frequency intensities of an image. If an image falls within the range of training set results, it is likely to be a pornographic image. The last process is HCM based on human skin detection. The experimental results show an effective accuracy after testing. This would demonstrate that our hierarchical image filtering techniques can achieve substantial improvements.

Keywords: Content-based Web Filtering, Image Filtering, Normalized R/G ratio, Histogram, Human Skin Detection

1. Introduction

Current implementations of web filtering use the techniques of URL blocking (black-list and white-list), keyword blocking, and rating system. Yet, web filtering system based on these three techniques are insufficiently accurate and do not cope well with the ever-changing web. URL blocking uses *a list of URLs* [1] and there are two types of list that can be used: black-list and white-list. The black-list contains URLs that must be blocked. It is a class of inappropriate web sites. The white-list on the other hand, contains a list of permissible sites. The main problem with URL-blocking is that new sites emerge quickly and continually. Therefore, it is difficult to maintain complete and up-to-date lists. Keyword filtering [1, 2] uses *a list of keywords* to identify undesirable web pages. If a page contains a certain number of keywords found in the list, it is considered undesirable. However, the main problem of this method is over-blocking since the meanings of words may depend on the context. For example, a site of sex education may be blocked because of the occurrence of the word "*sex*". In addition, the system is easily defeated using words intentionally or unintentionally misspelled. For example, a malicious site can replace the word "pornographic" with "pornographic" to thwart the filtering system. Such replacement will have little effect on the readability of the page by the user, but it will make keyword filtering significantly more difficult. So, a content-based analysis technique [1] is of interest for the web filtering task. It is well-known that pornographic web sites contain many sexually oriented texts, images, and other information that can also help to filter them. Image filtering, a kind of content-based filtering, is a much more intelligent and dynamic way to filter the pornographic web sites. There is rich information conveyed in images. Indeed, images are the main media used to propagate harmful information like pornography and violence. In general, the idea is to use the proportion of skin-colored pixels to other pixels to detect unwanted images. By using this technique, most pornographic images can be filtered out. In order to progress in analyzing the content of images, other information has to be extracted from the image.

In this paper, we propose a content-based web pornography filtering and image processing system to detect and filter inappropriate web sites. Our system consists of three main processes: filtering by normalized R/G ratio [3, 4], histogram [5], and filtering by matrix composition based on skin detection [6]. The first process is using the pixel ratios, since the normalized R/G ratio uses two color channels (red and green) for consideration. Next, histogram analysis is used to estimate the frequency intensities of an image. If an image falls within the range of training set results, it is likely to be a pornographic image. The last process is human composition matrix, based on human skin detection. In our system, if the normalized

R/G ratio can not block the web sites based on image content, they will be passed to the histogram analysis and the matrix composition based on skin detection, respectively.

The rest of paper is organized as follows. In section 2, the details of our methodology are described. Our experimental results and discussion are presented in section 3. Finally, we provide conclusions.

2. Research Methodology

The details of our content-based image filter methodology are shown in fig. 1. Our system consists of three main processes: normalized R/G ratio, histogram analysis, and matrix composition based on skin detection.

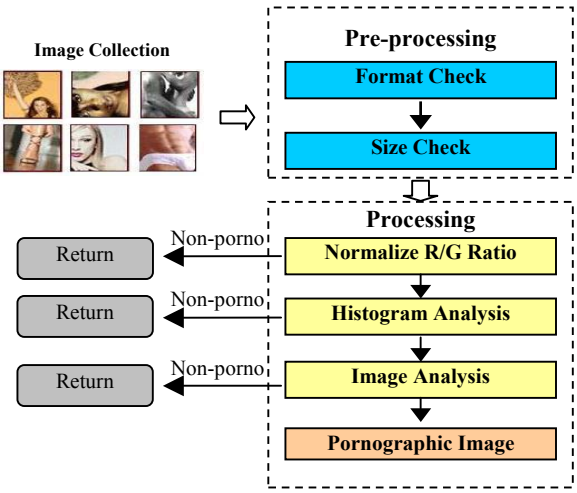


Fig.1: Research Methodology

In order for a web page to be analyzed by the image processor, the image types must be JPG/JPEG, BMP, PNG, or PCX. Furthermore, the image sizes must be in the rage of 50x50 pixels and 1300x1300 pixels. After that, the web sites are passed to image-content filter.

2.1. Normalized R/G Ratio

In the previous study of image processing, normalized RGB [3] is a representation, which is easily obtained from the RGB values by a simple normalization procedure:

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B} \qquad b = \frac{B}{R+G+B} \qquad (1)$$

The sum of the three normalized components is known ($r+g+b = 1$). For the dependence of r and g on the brightness of the source, RGB color is diminished by the normalization. However, it was observed that skin invariably contains a significant level of red and green (especially *red*), and using this observation, certain values of R/G ratio were used as skin presence indicators [4]. Therefore, in this work, we apply only two color tones (red and green) for image analysis, since the R/G ratio is significant in many skin colors, including those that are commonly found in African, Asian, and Caucasian skin.

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B} \qquad (2)$$

Let L_{lim} be the lower bound of human skin and U_{lim} be the upper bound of human skin.

$$L_{\text{lim}} < R/G < U_{\text{lim}} \qquad (3)$$

In this work, we use $\boldsymbol{L}_{\text{lim}} = 1.0559$ and $\boldsymbol{U}_{\text{lim}} = 1.8617$ that were calculated from prior images (1,000 pornographic images and 1,000 non-pornographic images) by mean value of R and mean value of G. The ratio of these means (R/G) is the *normalized* R/G ratio. Furthermore, the pornographic image data and non-pornographic image data are sorted. We have found that the R/G ratio of a non-pornographic image typically has the normalized R/G ratio as an upper bound, while a pornographic image typically has the normalized R/G ratio as a lower bound.

If a web site is not blocked by the normalized R/G ratio comparison phase, it is passed to the next phase, which is histogram analysis.

2.2. Histogram Analysis

In image processing, a histogram is a graph demonstrating the number of pixels in an image at each different intensity value of that image [5]. Let $HR(i)$ be the color histogram of image i. An image can then be represented by a feature vector H as follows:

$$H = \{ HR(1), HR(2), ..., HR(M) \} \qquad (4)$$

If some of images are in the range of training set results, they may be pornographic images. Afterwards, they will be processed using Image Analysis.

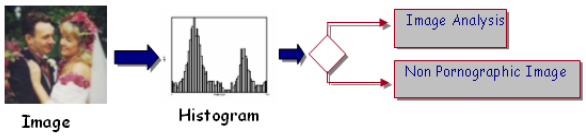


Fig.2: Image Analysis by Histogram

If the web sites can not be blocked by histogram analysis, they will be passed to the next process, the human composition matrix based on human skin detection.

2.3. Human Composition Matrix based on Human Skin Detection

In this process, we propose a new technique for pornographic web site filtering. It is called the *Human Composition Matrix (HCM*). If a web site contains several nude images, HCM decides that the web site should be blocked. We have found that HCM is effective at detecting pornographic images, and it does not take much time.

The first step in HCM is to segment the image into a square matrix, usually having dimensions 6x6 (as shown in Fig. 3). We actually test more matrix sizes such as 3 x 3, 4 x 4, 5 x 5, 6 x 6, 7 x 7, 8 x 8, and 9 x 9. The empirical results show that the 6x6 matrix size is most effective for this task. The HCM technique then considers each image in the square matrix format.

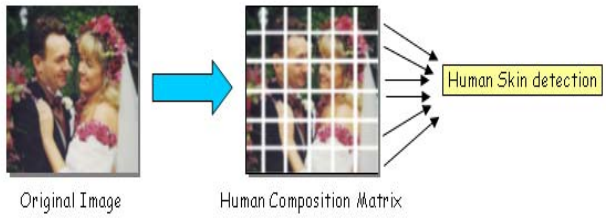


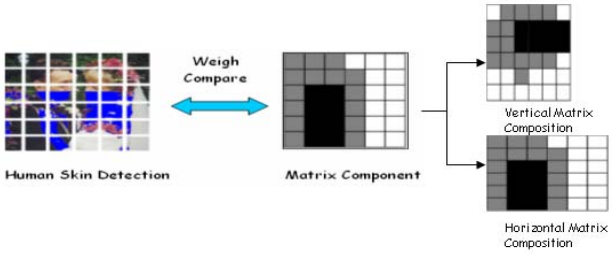
Fig.3: Human Composition Matrix

After an image is in the square matrix format, it is analyzed using human skin detection technique. Human skin detection [6] is done by detecting human skin pixels in an image. The output is a binary image defined on the same pixel grid as the input image.

A labeled classifier training set is used to construct skin and non-skin color models for each block. Skin and non-skin histogram models are built using the classifier training set of images. Given skin and non-skin histograms, the probability that a given color value belongs to the skin and non-skin classes can be computed using the formula of Jones and Rehg [6] as follows:

$$\boldsymbol{P(rgb|skin)} = \boldsymbol{s}[rgb]/T_s \quad P(rgb|\neg skin) = n[rgb]/\ T_n \qquad (4)$$

where $s[rgb]$ is the pixel count contained in bin rgb of the skin histogram, $n[rgb]$ is the equivalent count from the non-skin histogram, T_s and T_n and are the total counts contained in the skin and non-skin histograms, respectively. After that, a ratio of skin and non-skin histograms is calculated and we use the skin ratio for image analysis. However, we will consider in three classes of human skin: high, medium, and low of skin tones (as shown in Fig. 4).



where

The block that contains the highest of skin pixels.
The block that contains the medium of skin pixels.
The block that contains the lowest of skin pixels.

Fig. 4: Human Skin Detection

Finally, we use this template to analyze and filter any images for our pornographic web filtering system.

3. Experimental Results

In order to observe characteristics of our system, we gathered 4,000 pornographic images and the other 4,000 non-pornographic images for our experiment. We then randomly selected 1,000 pornographic images and 1,000 general images as a training set. Afterwards, we and histogram. This would demonstrate that the HCM can achieve substantial improvements. HCM is based on skin detection model, which is built from a skin pixel-probability or skin pixel count approach. So, it can classify an image to a class according to the skin pixels appearing in the image content, together with the probabilities of the skin pixels learned from a training set. A strong assumption of this approach is that the quantity of interest is governed by the distribution of skin pixel probabilities, and the skin pixels in the image are independent from one another.

Table 1: Testing with 2,022 pornographic images and 1,581 non-pornographic images.

Algorithms	Pornographic Images Effectiveness (%)		Non-pornographic Images Effectiveness (%)	
	Correct	Incorrect	Correct	Incorrect
R/G Ratio	90.60	9.40	68.67	31.31
Histogram	89.00	4.00	80.50	19.50
HCM	94.20	5.80	99.67	0.33

In addition, we tested the hierarchical image filtering system to filter the web sites on WWW. We used 401 pornographic web sites and 314 non-pornographic web sites for testing. The results are shown in Table 2.

Table 2: Testing with 401 pornographic web sites and 314 non-pornographic web sites.

Websites	Effectiveness (%)	Over-blocking[1] (%)
Pornographic websites	92.03	0.00
Non-pornographic websites	95.00	5.00

4. Conclusions

In this paper, we have built and examined a pornographic web filtering system based on image content. Our system consists of three main processes: (i) normalized R/G ratio, (ii) histogram, and (iii) human composition matrix based on skin detection. The first process is normalized R/G ratio, which is the ratio of RED and GREEN from an image. $L_{lim} < R/G < U_{lim}$, where L_{lim} is the lower bound of human skin and U_{lim} is the upper bound of human skin. In this work, we use $L_{lim} = 1.0559$ and $U_{lim} = 1.8617$ that are calculated from prior images. When we pass a web site to the system and it is not blocked by this process, the web site will be passed to the next process (histogram analysis). In histogram analysis, we use this technique to estimate the frequency intensities of an image. If an image is in the range of training set results, it may be a pornographic image. However, if the web site is not blocked by histogram analysis, it will be passed to the next process. The last process is the human composition matrix based on human skin detection. It will consider each image in the square matrix format. Each image is then separated into 6 x 6 matrixes. After that, the human skin detection technique is applied. We consider in three classes of human skin: high, medium, and low color tones. Finally, HCM yields a result in a template format for image filtering. After testing, The HCM model shows a higher accuracy than the normalized R/G ratio and histogram. After testing the system with real-world data, the system was sufficiently accurate. This demonstrates that our proposed techniques can provide more effectiveness for pornographic web filtering based on image content.

[1] If a general web site is analyzed as a pornographic web site, it actually is not. This problem is called ***over-blocking***.

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5. References

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