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A Statistical Algorithm Approach for Explicit Image Discretion

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Abstract: A novel two stage multiple parameter statistical algorithm to identify pornographic images is proposed in this study. In the current study we present an analysis on various color spaces to identify an optimal color space for human skin pixel identification. A new algorithm is proposed to identify and avoid the explicit image by considering high skin pixel rate. The proposed algorithm was tested in terms of accuracy, true negatives and false positives and the experimental results presented in the current study show that the algorithm worked well and fast in detecting pornographic images.

Key words: Human skin tone, color spaces, saturation image, face detection, skin pixel identification

INTRODUCTION

In recent years numerous methods have been implemented to block or avoid explicit images or videos in public domain like the internet. The internet usage has burgeoned by leaps and bounds in recent past. The data analysis done reveals that nearly 40% of the world population has started using the internet. The content scanning in terms of explicit contents such as text, images and videos is very much in need because majority of internet users are adolescents and teenagers. The major category which falls prey to pornography is the educational community (Ding *et al*., 1999). The introduction of android based devices and applications related to web services has worsened the scenario (Chen *et al*., 2013). Statistics on internet content by several organizations shows that >30% of the content on the internet is pornographic. The content in mobile internet is also steadily rising towards 4 billion.

The processes of blocking such content have been implemented in most countries and sectors. The earlier works were purely based on URL or the text contents of the website. These methods involve division of URL's into 2 classes such as suspicious and normal (Yin *et al*., 2011). These methods proved to be effective initially but currently the violators have started to upload adult content such as images and videos without such suspicious terms. Thus identifying pornographic images and videos by analysis of the content itself has become imperative. Many research works have been done in this direction over the years. Figure 1 shows the basic model of pornographic image discretion in which the input image is scanned for skin pixels. Feature extraction is done based on the shape of the area detected and the texture of the skin pixel regions. The image classifier will discriminate the images as good and explicit based on predefined threshold values (Hu *et al.,* 2007). In the proposed algorithm, pornographic images are discriminated with a statistical skin pixel proportion approach. The main contributions of this study are:

- Comparative analysis of skin pixel in various color spaces
- Discrimination of facial and non-facial images
- Adaptive statistical threshold calculation for classifying pornographic images

Literature review: Many research works have been already done on adult image identification. The available literature reveals that the methodology for skin pixel based image discrimination can be categorized into two types, namely physical structure based approach and statistical based approach. The shape features were extracted and fed into a boosted classifier to decide whether or not the skin regions represented nudity, based on skin color detection (Zheng *et al*., 2004). An algorithm which used subsection processing skin color filtering to filter the non-skin color pixels, coarse degree based texture filtering to filter pixels with rough texture and skin color tone and fractal dimension filtering to filter the skin like region (such as deserts or beaches) is analyzed (Yin *et al*., 2011). An algorithm to investigate the utility of static anthropometric distances as a biometric for human identification is proposed (Godil *et al*., 2003). The use of a fast and precise neural model, called Multi-level Sigmoidal Neural Network (MSNN) was discussed (Sadek *et al.,* 2009). A texture model based

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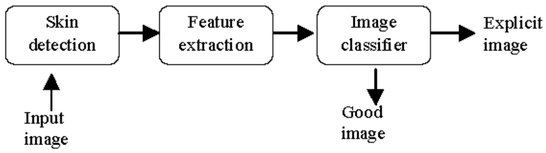

Fig. 1: Basic model of pornographic image discretion

on Gray Level Co-Matrix (GLCM) and geometric structure of human beings to classify pornographic images is done (Zhu *et al.*, 2007).

Similarly a number of works have been done with statistical based classification for adult image discrimination. An algorithm which could effectively detect the ROIs (Region of Interest) with plentiful skin information. In the above method, the image was classified into different segments and for each segment the ROI was analyzed. Based on the results the reliable feature was obtained for image classification (Yang *et al.*, 2004).

An algorithm is proposed in which the ROI was first located by detecting skin-like pixels in YCbCr color space (Fu and Wang, 2011). It was then classified into being acceptable or unacceptable based on its size using SVM classifiers. A model analyzing the HSV with Newton's law of center of gravity of colors was studied. It also uses a face detection to evaluate the pornographic content in an image (Zhao *et al.*, 2008) All the approaches stated above failed to determine the:

- Images with facial contents
- Images with partial explicit content
- Images with high level of illumination

This study proposes an efficient algorithm which addresses the above said issues by improving the following parameters:

- The accuracy of skin pixel identification
- Prediction process for classifying porno images

MATERIALS AND METHODS

Comparative analysis of existing methods: In most of the models proposed, the overall process can be put in to two parts. In the initial part the skin pixels are identified. The later part discusses the decision making algorithm which may be derived based on shape and structure of the skin pixel groups or based on the statistics of the skin pixels. The presented work follows the latter for its simplicity and guaranteed results.

The proposed method focuses on two sets of analysis. Initially, the study about various color spaces which best suits skin pixel identification and later the study about various algorithms for classifying explicit images.

Skin pixel detection on various color space: The color range of human skin lies between dark brown and light pinkish hues. The human skin tone has a unique color value compared with the colors of all other objects. Only very few objects fall in the domain of skin tones hence skin pixel identification using pixel color value best suits the requirement. There are many color spaces in which the analysis can be done. Some of the major color spaces are RGB, HSV, YCbCr and YIQ. Many proposals have been made in identifying skin pixels in an image. This is usually identified by the pixel value and verifying its presence in the human skin pixel region. The performance of a particular method is identified by the accuracy measured by the false detections such as false positive where non-skin pixel is detected as skin pixel and true negative where skin pixel is identified as non-skin pixel.

The results of RGB color space gets affected when the image is an illuminated imag (Osman *et al.*, 2012). Another research work clears that other color spaces such as YCbCr, YIQ and HSV neglects the effect of the illumination (Jedynak *et al.*, 2003). Segmentation done on the image and color distance map is used to determine skin pixel region and non-skin pixel regions reliably (Abdullah and Chae, 2008). However, the results based on segmentation fails under chrominance channels (Phung *et al.*, 2005). There are other areas of concern also for skin pixel identification such as regional based skin tone variations which has not been addressed in many works.

Classifying explicit and non-explicit images: In terms of decision making or prediction once again the parameters such as false positives and true negatives are involved. There are various algorithms proposed for discriminating explicit image from non-explicit image using skin pixels of image in statistical method. The research proves that skin pixels and discretion process is just percentage of skin pixels in the overall image (Basilio *et al.*, 2010). It is the simplest but fails miserably for facial images or images with small areas of explicit nature. The ROI can be easily located by detecting skin-like pixels in YCbCr color space (Paul and Gavrilova, 2011). The ROI is then classified into being acceptable or unacceptable based on its size. The method once again does not make it clear whether the images of complete face or just the back of the body should also be considered as explicit. This problem is addressed by designing a model by applying Newton's

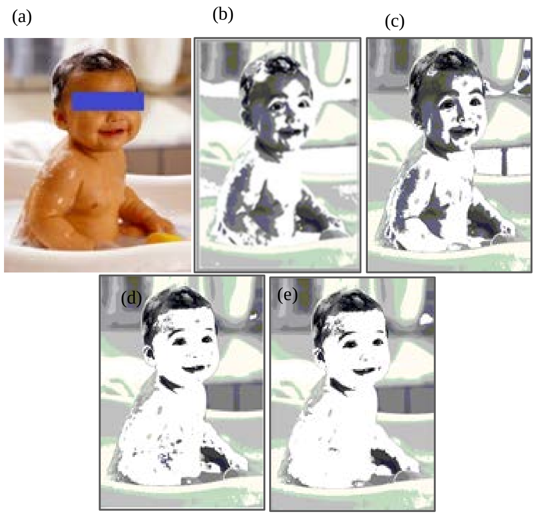

Fig. 2: Results under illumination condition: a) Original image; b) HSV result; c) RGB result; d) YIQ result and e)YerCr result

law of center of gravity of colors and a face detection process to find the amount of explicit content in a given image (Zhao *et al.,* 2008). A similar approach is made which employs an ancillary technique for studying the Human Body region using shape, color and image centered pixel scanning analysis (Choi *et al.,* 2009) however, both go on the same lines with respect to location which will generate more true negatives if the image has explicit content at the sides.

At the end of the analysis it becomes clear that if the following two problems are addressed, the resultant model will provide high valued results:

- Color space which best suits for skin pixel identification
- Illumination avoidance
- Irrespective of regional skin tone
- Formidable algorithm for discrimination of explicit images

Proposed method: In order to address the above said conditions, the proposed algorithm takes up the work of analyzing RGB, YCbCr, YIQ and HSV color spaces. The skin pixels are discriminated with the individual pixel values. There is a boundary value for skin pixels in every color space. The boundary values of each color space are evaluated by using the 3D histograms of those color spaces. The skin pixel boundary value for various color schemes lies in the region as described here.

RGB is the basic color space which describes the pixel value based on composition ratio of Red (R), Green (G) and Blue (B) intensities. The pixel values lies in the region of :

$$120<R<250;\ 70<G<190;\ 50<B<160$$

HSV is sometimes referred to as HSB and it generates pixel value based on the composition of Hue (H), Saturation (S) and brightness level (V) of the pixel. It provides more a natural description of an image. In this color space, the components and the region of skin pixels is defined as follows:

$$0<H<20;\ 0.2<S<0.75;\ V>0.35$$

YIQ is one of the most popular color schemes which was used in broadcasting of television signals. The pixel value is provided with luminance (Y) and two chroma values. The two chroma values are based on blue (I) and red (Q) compositions. The skin pixel region under YIQ color space is described here:

$$0.2<Y<0.9;\ 0.01<I<0.18;\ Q>0.0$$

Under normal conditions the identification of skin pixel is more or less similar in all the color spaces but under illumination condition the RGB fails miserably as shown in Fig. 2.

The results show that the YCbCr responds well under illumination conditions. To address the regional skin tone issue the algorithm uses an image where all the regional skin tones are present such as Asian, European and African.

Proposed algorithm: The proposed model differs from the other ones by the internal key factors and flow of statistics which have been modified to improve the results. The entire process consists of three stages: The skin pixel identification is done in the initial stage. While the middle stage provides the data's of face detected from the original image. The final stage classifies the pornographic images and the non-pornographic image with the data availed from the first two stages.

Stage 1: In this process, the input RGB image is scanned and then the image is converted into an YCbCr image. From the YCbCr image the individual pixel values are calculated and they are compared with the skin pixel values. If they match then the skin pixel count is incremented by one. If not, then checking for the other pixels is done. This process continues until the last pixel of the image is reached. The flow chart in Fig. 3 explains the above mentioned process of identifying skin pixels.

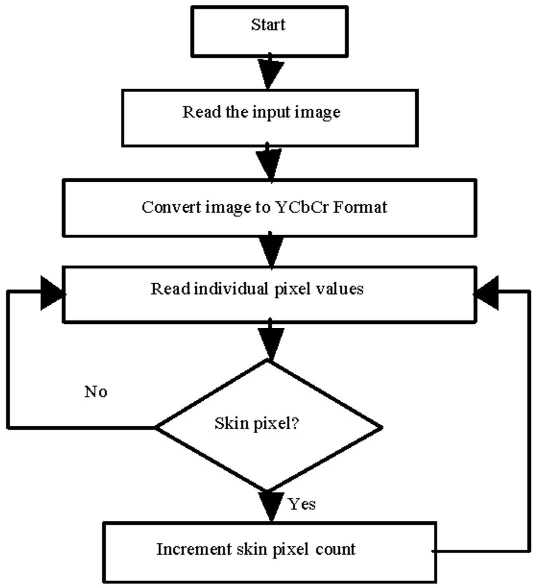

Fig. 3: Identifying skin pixels

Stage 2: In this process, the in depth details of the type of image content are analyzed based on which the prediction process becomes more accurate. The structural details of the humans available in image are retrieved from the original image. If humans are detected, then the process continues to check for the presence of human faces. Figure 4 explains the process of facial image identification by means of a flowchart. Initially from the original image the algorithm retrieves the structural details of the humans available in it. If humans are available then we check for the presence of faces. Finally, if the image has faces, then the algorithm calculates the total number of faces available and the facial pixel count. This data will be used in the prediction process for decision making.

Stage 3: In this process, the data collected from the first two stages are analyzed and based on the analysis the validity of the goodness of image content is measured. It has multiple checkup process. The process of decision making is portrayed as a flowchart in Fig. 5. The algorithm first checks the image for the presence of human faces in it. If it does not contain any faces then the purity of the image is decided with just ratio of the skin pixel count with respect to the total pixels. In case of facial images the ratio of facial pixels is found with respect to the total skin pixels count. From the results the image is categorized as an adult image or facial image or good image.

Implementation: The entire process of implementation can be easily analyzed by the block diagram shown in Fig. 6. The complete process of the proposed algorithm

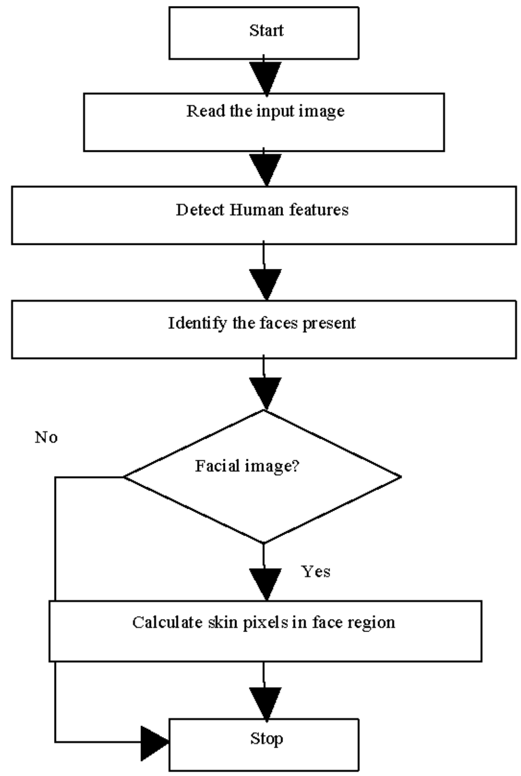

Fig. 4: Facial image identification

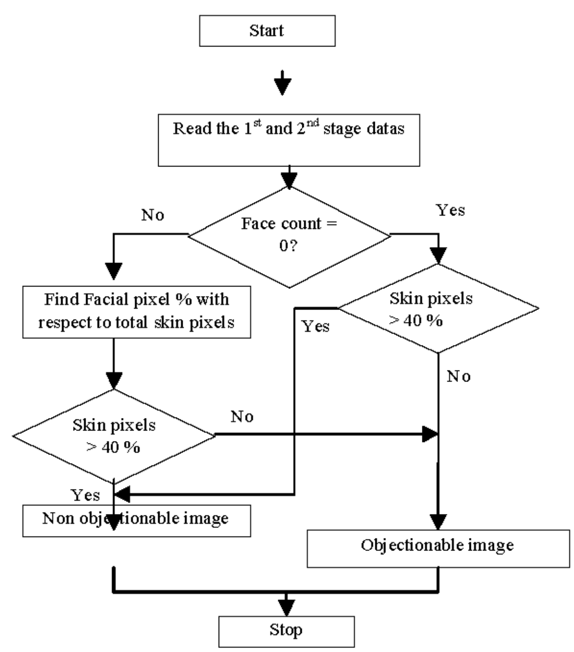

Fig. 5: Decision making process

has been implemented and analyzed using MATLAB software. The process is split into 3 stages:

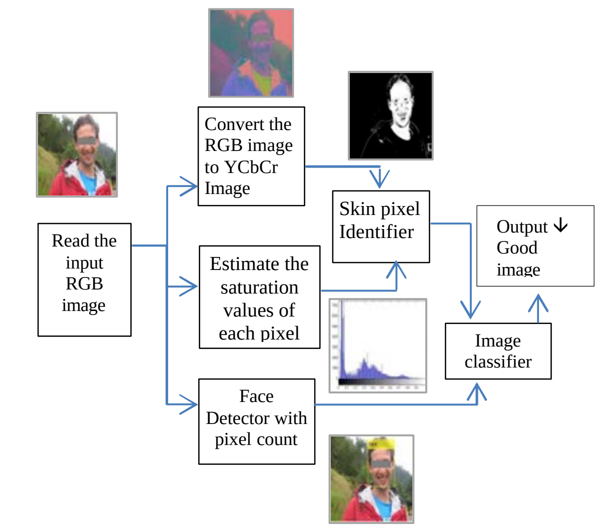

Fig. 6: Overall implementation block diagram

- Skin pixel identification
- Face detection
- Image classification

Skin pixel identification: This process involves two levels of discretion for gaining higher accuracy in identifying skin pixels even under illumination. The first level involves the YCbCr mapped pixel value comparison and the second level removes the false pixels using saturation rates of the pixels. The conversion stage of RGB to YCbCr is implemented using following formulae:

$$Y = 0.299\ R+0.587\ G+0.114\ B$$

$$Cb = -0.168736\ R-0.331264\ G+0.5\ B$$

$$Cr = 0.5\ R-0.331264\ G-18.214\ B$$

Once the image is converted, the YCbCr image is put for pixel scanning such as X(i,j) pixel of image at (i,j) th location. The pixel values are compared with the region of human skin pixels with below mentioned limit conditions:

$$Y(X_{ij})> 80;\ 85<Cb(X_{ij})<135;\ 135<Cr(X_{ij})<180$$

The pixels which fall into these limits are made white pixel and the count of the skin pixel "sp" is incremented. The other pixels are left alone.

Estimation of saturation: The saturation values provide a very good suppression for false positive pixels occurring due to illumination factor. It can also provide the clear boundary for skin pixels of people from African regions. The implementation has to generate a histogram of saturation values of the given image. First, the 2D saturation image of the original image is retrieved from which the mean saturation value can be deduced. The saturation image can be prepared considering the R, G and B values of the image.

The saturation value is the ratio of difference between the maximum and minimum value of pixel to that of the maximum value of the pixel. Once the saturation image is prepared, we deduce the histogram of the image and calculate the mean value. This saturation value is used to remove false pixels from the skin pixels and with that the final skin pixel count is evaluated.

Face detection process: The face detection process explains whether the image contains any face in it as well as the number of faces and the count of pixels in the face region which is denoted as facial pixels. There are many algorithms to detect face in an image it uses Viola Jones algorithm to detect faces in the image.

The Viola-Jones method starts with the process of feature selection with which integral image is made over which the Adaboost algorithm is applied. Multi stage classifiers helps in discretion of the features of humans.

For this face detection first it tries to find the eye pairs present in the image. Once the eye pair is identified, we can plot a rectangle around the eye region based on the distance between the eyes. Once the face regions are identified and marked, the pixel count 'fc' of those regions is calculated.

Image classification: This process determines whether the given image is explicit or good. Based on the research questions, it has to clearly differentiate the images without any false positives such as images only with face and some part of the shoulder cannot be an explicit image. At the same time if the image does not have face but shows some adult content, then that should not be declared as good image.

To establish such discretion the algorithm uses the following process. From the face detector it finds whether the image has face or not. If so it takes the face pixel count fc and compares it with overall skin pixel count sp. If face pixel is <30% of the total skin pixel, then it declares the image as explicit since the face constitutes only a fair part hence the remaining skin pixels might be adult content. This can be extended to multiple face images also.

On the other hand, if the face detector does not find any face, then we find what percentage of total pixel is skin pixel. If it exceeds 50% of the total pixel, we declare them as explicit images.

$$|\ \text{Explicit Image}\ | = \begin{cases} \dfrac{Fc < 0.25Sc}{Sc > 0.5Tc} \end{cases}$$

Where:
F_C = Face pixel count
S_C = Skin pixel count
T_C = Total pixel count

RESULTS AND DISCUSSION

Initially, for the purpose of evaluating the color spaces, the images with different backgrounds are used such as blank background and backgrounds that are very close to skin tone. On the analysis of the skin pixel identification the effectiveness is measured on various parameters such as True positive, true negative, False positive and false negative. Figure 7 shows the results of skin pixel identification using various color spaces. The white spots in the images show the skin pixels being identified. The following image was chosen under illumination condition.

As seen from Fig. 7 that, RGB color space provides very high false positives revealed by the fact that even the dress is considered as skin pixel. The same is true in the case of HSV but its extent is a little less than that of RGB. The output of YIQ clearly shows that it missed a large percentage of skin pixels as well as it detected the dress pixels as skin pixels. The plots shown in Fig. 8 reveal the pixel count generated by different color spaces in the given image. Figure 9 shows the plot of various criteria such as error value true negatives and false positives

Figure 8 indicates the amount of skin pixels detected using the different color spaces and also compares it with original pixel count. The graph reveals that HSV has the maximum pixel count. Figure 9 shows the error pixels picked by different color spaces. It also reveals that HSV and RGB color spaces produce high error but YIQ has very less error value but the plot in Fig. 9(c) clearly shows that its True negative is very high which is not all tolerable for the given application.

Table.1: Results under normal circumstances

Algorithms	True positive (%)	False positive (%)	True negative (%)
Gang Zhao	90.0	41.0	10.00
CBIR	68.2	64.5	12.05
Balamurali	85.4	35.0	16.43
Proposed Algorithm	95.6	15.4	6.200

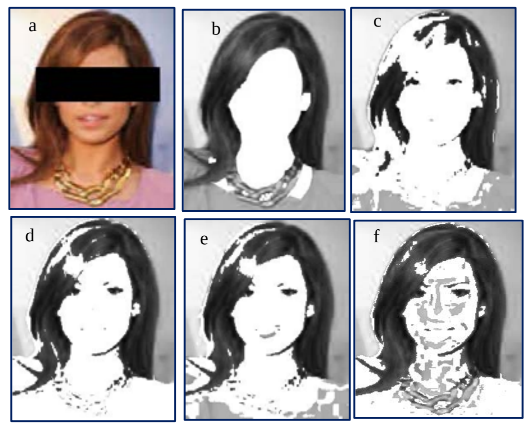

Fig. 7: Results of skin pixel identification: a) Original image; b) Orignal skin pixel; c) RGB result; d) HSV result; e) YcbCr results and f) YIQ results

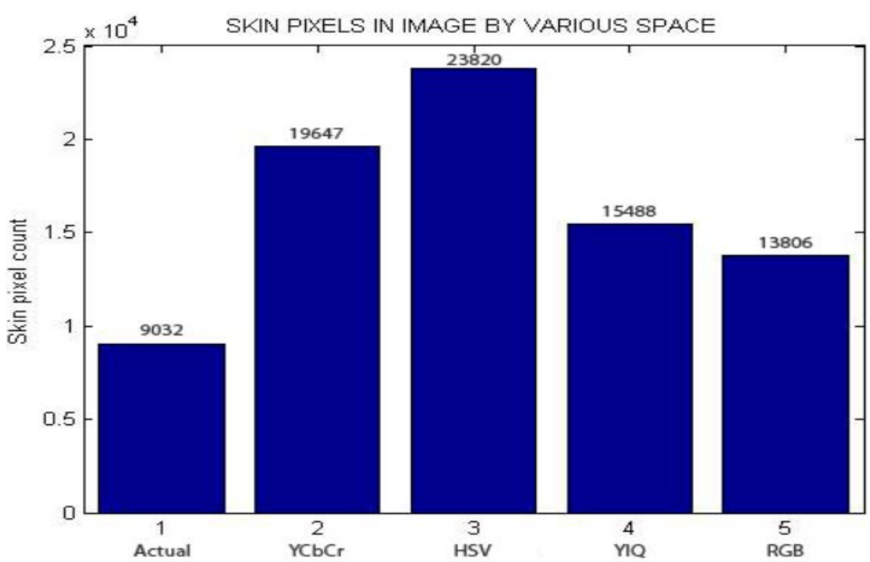

Fig. 8: Skin pixel count

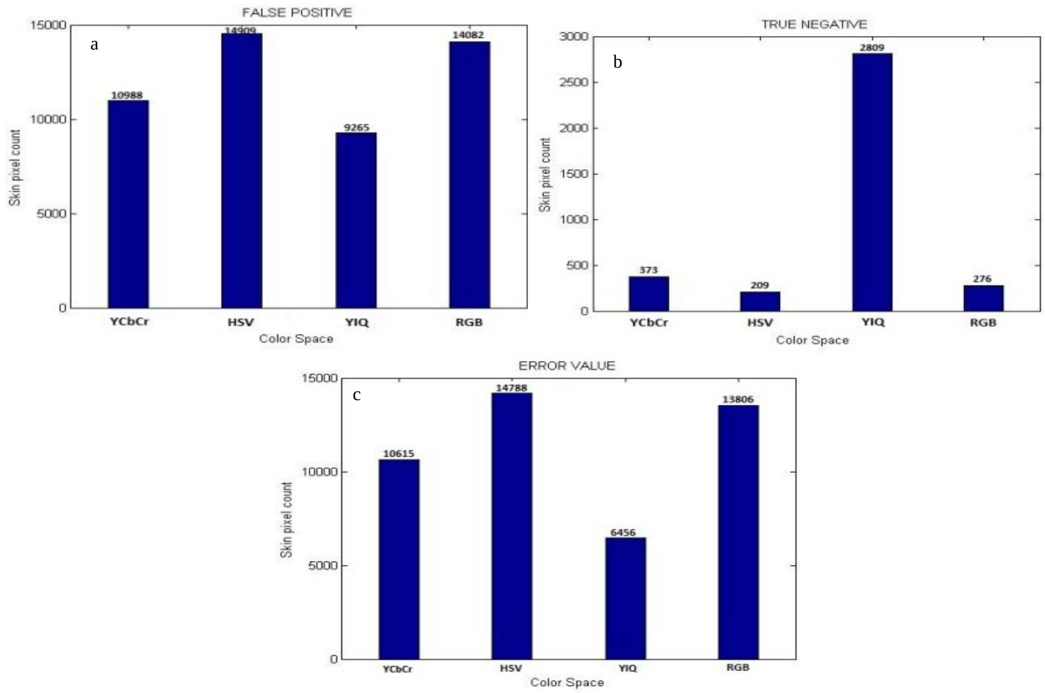

Fig. 9: Results of skin pixel identification on various criteria: a) Error value; b) True negative; c) False positive

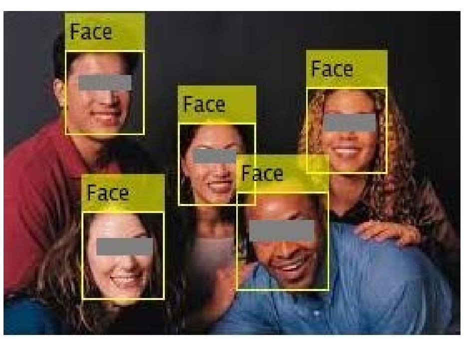

Fig. 10: Face detection using Viola Jones algorithm

Figure 9b indicates that YCbCr has very nominal false positives which are acceptable given the status of error and true negatives. These results clearly show that YCbCr color space is best suited for the proposal. In the decision making algorithm as explained in the previous section the face detection procedure is carried out using "Vision Cascade Object Detector" object in MATLAB which uses Viola-Jones algorithm. Figure 10 depicts one of the results of the detector.

Figure 10 clearly shows that the algorithm is tolerable with change in angle of face and that multiple faces can be clearly differentiated and detected. Figure 11 shows the proposed algorithm's results for blocking the objectionable images and allowing the non-objectionable images.

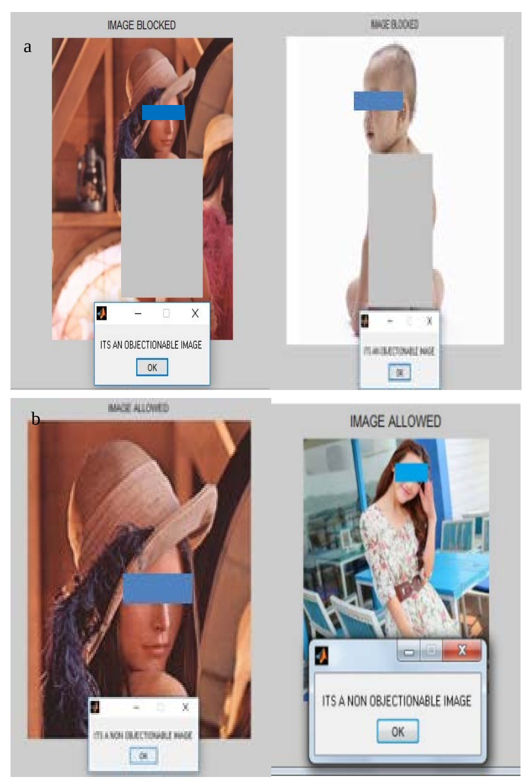

Fig. 11: Simulation results of image discretion: a) Objectionable image blocked; b) Image allowed

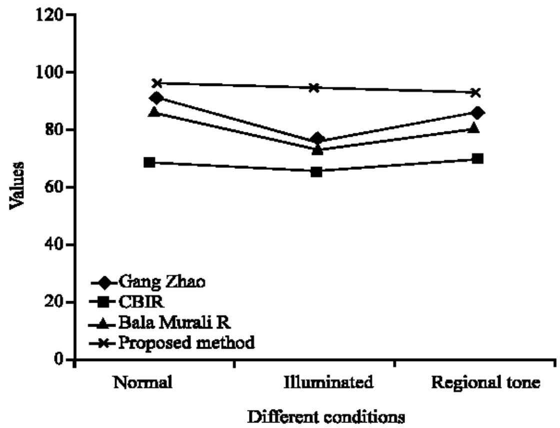

Fig. 12: True positive under different conditions

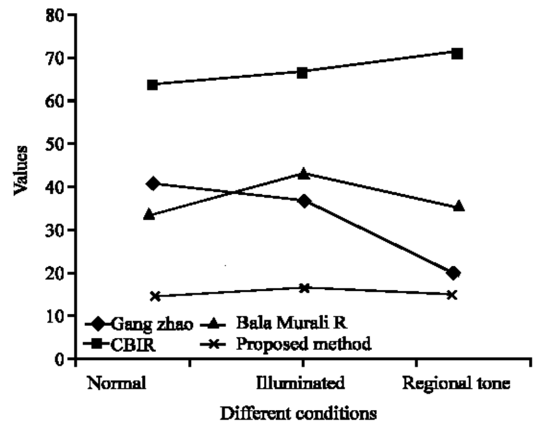

Fig. 13: False positive under different conditions

Table 2: Results under illumination circumstances

Algorithms	True positive (%)	False positive (%)	True negative (%)
Gang Zhao	74.60	37.0	37.5
CBIR	65.67	67.0	14.5
Balamurali	73.40	43.6	29.8
Proposed algorithm	94.72	17.2	8.60

Table 3:Results under illumination circumstances

Algorithms	True positive (%)	False positive (%)	True negative (%)
Gang Zhao	85.40	20.2	43.2
CBIR	68.90	72.0	37.3
Balamurali	80.20	36.7	39.5
Proposed algorithm	92.35	15.6	12.9

For the decision making process an image database of nearly 300 images with 50% of fully nude images and 25% of half nude images and 25 % of Good images were taken and the results are plotted for accuracy in terms of true positive, false positive and true negative. Table 1 shows the comparison of results obtained from the proposed method with other works.

Similarly the database was replaced with multiple illuminated images as well as images with poor lighting. The results for this database are shown in Table 2 which varied with great significance and proved vital for the support of the proposed algorithm. In the process, the Asian and African ethnicities were also included with other color tone images for which the results obtained are shown in Table 3.

From Table 1and 2 a plot was obtained between different methods on the basis of illumination and region based skin tones which revealed that the proposed algorithm performed well in both the conditions (Fig. 12-14).

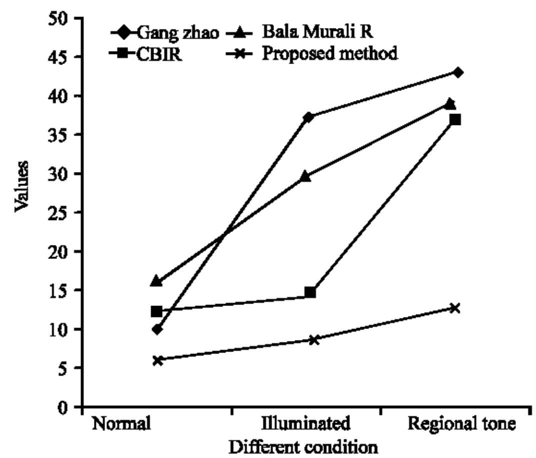

Fig. 14: Plots on performance of various methods under different conditions

CONCLUSION

Thus, a novel two stage multiple parameter statistical algorithms to identify pornographic image was proposed and implemented. The approach had two stages: firstly analysis on different color spaces was done and YCbCr was found to be the optimal color space for skin pixel identification. Secondly, the face detection algorithm was used in classifying the explicit images. The classification was statistical based and different logics were used for images with face and without face. The proposed algorithm was implemented in MATLAB and the simulation results showed that this method had better true positives, optimal false positive and very low true negatives. This method can be further improved with better face detection process for tilted faces and angled faces.

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