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Fast Pornographic Image Recognition Using Compact Holistic Features and Multi-Layer Neural Network I Gede Pasek Suta Wijaya a,1,*, IBK Widiartha a,2, Keiichi Uchimura c,3, Gou Koutaki c,4, M Samsu Iqbal b,5, Ario Yudo Husodo a,6 a Informatics Engineering Dept., Mataram University, Jl. Majapahit 62, Mataram, Lombok Indonesia b Electrical Engineering Dept., Mataram University, Jl.

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ABSTRACT (10PT)

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The paper presents an alternative fast pornographic image recognition using compact holistic features and multi-layer neural network (MNN).

The compact holistic feature of pornographic images, which is pose and scale invariant information, is extracted by shape and frequency analysis of skin region of interests (ROIs) of pornographic images. Main aim of this research is to design pornographic recognition scheme which not only can improve performances of existing methods (i.e.

methods based on skin probability, scale invariant feature transform, eigenporn, and Multilayer-Perceptron and Neuro-Fuzzy (MP-NF)) but also can works fast for recognition. The experimental data show that our proposed method can increase accuracy by about 4.32% and decrease the FPR by about 14.65% of the best existing method (fusion descriptor, FD), respectively.

In addition, our proposed method also provides almost similar robust performances to the MP-NF on large size dataset. However, our proposed method needs very short recognition time by about 0.021 second per image for both tested datasets. 

Keywords Pornographic image Recognition system Neural network Holistik features Frequency analysis

Introduction The blocking of pornographic contents (images, video, and text) become hot issues in undeveloped countries like Indonesia due to their many negative effects, especially for children and teenagers. The report in 2005 mentioned that 25% of the queries in search engines, 8% of emails, and 12% of homepages related to pornographic contents[1].

Regarding the negative effects of pornographic contents, pornographic addiction is the most negative effect of accessing pornographic contents, which make the addict be flying due to pornographic contents. In addition, the pornographic contents also can trigger sex deviation behavior and early pregnancy especially to teenagers and children who do not have enough information about the negative effects of pornographic contents.

Therefore, a blocking system which can reject accessing pornographic contents is needed to decrease the negative effects of pornographic contents. In order to build a strong blocking system of pornographic contents, a good recognition algorithm is needed. In this case, the recognition algorithm determines the similarity between input image feature and the training set features, if the input image is matched (recognized) as pornographic content, it will be blocked to be viewed or displayed.

In order to contribute to the rejection of pornographic contents, an alternative pornographic image recognition using compact holistic features and the neural network is presented. The compact holistic feature which poses and scale invariant information of pornographic images is extracted by shape analysis and frequency analysis of skin region of interests (ROIs) of pornographic images.

The skin ROI has been proved that it can handle the large variability of pornographic images due to background variations[2], [3]. The classification based neural network based is employed to decrease the recognition time. The main aim of this paper is to design new scenario of pornographic recognition using compact holistic features representing the shape and dominant skin information which can improve the performance of existing methods (i.e. methods based on skin probability, eigenporn, Multilayer-Perceptron and Neuro-Fuzzy, etc.).

In this research, the performance indicators for examining our proposed methods are accuracy, false positive rate (FPR), false negative rate (FNR), and computational time. Previous Works The state of the art approaches to adult/pornographic image recognition which was divided into three main groups[4]: based on color, shape and local descriptor.

While other researches[1] also have grouped approaches to pornographic filtering into three major classes: (1) based on text contents, (2) based on collection lists of adult website addresses that is blocked by internet firewall, and (3) based on image content analysis[1], [2], [5]–[7]. Regarding texts content-based method, it classifies the material to be pornographic using the probability/entropy of texts related to pornographic contents that are available in the material (i.e. websites). However, this method fails to block material having many pornographic images and videos.

Next, the website URL based method rejects the accessing the adult image using internet firewall such as squid that has the rule to block the website addresses (URLs) list belonging to pornographic contents. However, adult website grows quickly and the website address can easily be renamed by the owner. Finally, the method based on image analysis performs the rejection of accessing website based on the images or videos that existing in the media.

This can solve the weakness of two former methods. As mentioned early, the last type of filtering method faces many obstacles because of the large variability of pornographic images due to pose, skin, lighting, and background information.

In addition, detection of pornographic images algorithms also can be grouped as based on contour, region[8], human skin probability[2], [6], [9], and scalable color, edge histogram, and shape descriptors[10]. Both contour and region of pornographic were extracted using skin color. Those methods were proposed to handle mentioned obstacles of pornographic image recognition.

However, they still have high false positive and negative data due to the large variability of pornographic images. Mostly, the skin models that were implemented for segmenting the skin region were threshold model in YCbCr, HSV, and RGB color space[2], [9] and Gaussian mixture models[8]. Regarding feature extraction techniques, they can be grouped into a holistic, shape, and local (eyes, nose, and mouth, genital) feature extraction techniques.

All of the feature extraction techniques were widely used because they can work quickly. The examples of holistic feature extraction techniques are content-based feature extraction using frequency analysis (FFT, DCT, and Wavelet), feature point descriptor using SIFT[11], [12], eigenporn of HSV ROI feature extraction[13], and descriptors of color, edge, and shape of pornographic images[10].

The most recent approach for pornographic recognition is a variation of Convolutional Neural Network (CNN) called as Deep Multicontext Network(DMN)[14]. In DMN frameworks, a deep CNN is applied to model fusion features of sensitive objects in images. It seems the DMN algorithm need a complex process which require a large computational cost.

The diversity of different approaches to pornographic recognition show that the pornographic image recognition is a difficult task due to the large variability of the images. It also means the pornographic image recognition still challenges the research topic. In addition, those approaches did not consider yet the computational time of the recognition process.

Therefore, an alternative solution to pornographic recognition problem using compact holistic features representing shape and dominant skin information and multi-layer neural network (MNN) is proposed to improve the established pornographic recognition methods. In order to know the performance of our proposed method, the experimental data will be compared to the established pornographic image recognition methods (i.e

skin probability, skin region [2], [8], [9], fusion descriptor of YCbCr ROI(FD), eigenporn of HSV ROI and Multilayer-Perceptron and Neuro-Fuzzy (MP+NF)[1]). Proposed Algorithm The diagram block of our proposed pornographic recognition is presented in Fig. 1. The main concern of this research is to design compact holistic features which consist of shape and dominant skin information of pornographic images.

The compact holistic features are extracted by moment and Discrete Cosine Transforms of skin region interest (ROI) of pornographic images. The classification process is performed using MNN. The main difference of this method to the eigenporn[12] and the MP+NF[1]is placed on the features and classification algorithms.

The eigenporn based method implemented the eigenporn extracted by PCA and k-nearest neighbor for classification and MP+NF based method implemented the multi features and Multilayer-Perceptron and Neuro-Fuzzy for classification.   Fig. 1 Diagram block of the proposed pornographic image recognition Features extraction The compact holistic features consisting of shape and dominant skin information are presented by vectors representing the global information of pornographic or non-pornographic images.

In this case, the compact holistic features, which are design to require limited memory space, are extracted from the chrominance components (Cb and Cr) of the input images. The intensity component (Y) is not included in the features because it is very sensitive to lighting variations. the Briefly, the features extraction starts from pre-processing, ROI extraction, and shape and frequency analysis.

Pre-Processing and ROI extraction The pre-processing process relates to image resizing and lighting normalization. The input image is scaled into size 256 pixels by keeping the height and width ratio to decrease the computational time of next process. In order to decrease the lighting effect on images, the histogram equalization is employed for normalization.

The skin pixels of images that have much lighting effect fail to be classified as a skin without lighting normalization. In other words, the histogram equalization is applied to handle large variability of lighting variations of the input images. Next, the ROI extraction is started from pixels-based skin classification to obtain skin tone image.

Some methods for pixel based skin classification are presented by authors[1], [9], [15], [16]. Among the existing methods, the best performance was provided by pixels based skin classification on YCbCr color space[9], [12]. Therefore, pixels based skin classification on YCbCr color space is employed for extracting skin tone of images as presented in Algorithm 1.

Algorithm 1 The process of skin tone extraction. Input : image matrix (im) Output : skinTone matrix Process: skinTone (im:rows; im:cols) r ( 0; g(0; b( 0; for i = 0; i < im:rows; i + + do for j = 0; j < im:cols; j + + do b ( im(I, j, 1); g ( im(I, j, 2); r ( im(I, j, 3); int cb ( int((( 0.1481(r ( 0.2908 (g + 0.4390 (b) + 128); int cr ( int((0.4391 ( r ( 0.3667( g ( 0.0714*b) + 128); if (cb > 77&&cb < 127)&&(cr > 133&&cr < 173) then skinTone(I,j) ( 1; else skinTone(I, j) ( 0; end if end for end for return skinTone; In this case, the Cb and Cr have 225 levels in the range of 16-240. These levels are extracted by the RGB to YCbCr transformation algorithm[17].

In addition, the morphological also included on this process to remove false positive skin classification. This model has been proved to provide better performance for recognizing the pornographic images[12]. The output example of skin tone extraction algorithm is given in Fig. 2. Fig.

2 The output example of skin tone extraction From the skin tone image, the ROI is extracted by using vertical and horizontal projection[12]. After obtaining skin tone, the ROI extraction is started from performing the vertical (rows) and horizontal (column) integral projection to know the coordinates having large of skin and non-skin region using. Secondly, the vertical and horizontal projection probability having less than a defined threshold is removed.

In this case, by trial and error, the best threshold can be defined as 0.25 of maximum vertical and horizontal projection probability. Thirdly, the skin tone is cropped using the x and y coordinates where the vertical and horizontal projection probability is thresholded. Finally, the cropped skin tone is mapped to the original image to get the skin ROI image.

In this case, the skin ROI itself is implemented to remove non-skin information pornographic images and to decrease large variability of pornographic images due to background variations. Shape and Frequency Analysis Frequency analysis has been implemented to extract holistic features of an image such as a fast Fourier transform and Discrete Cosine Transforms (DCT)[1], [11], [12].

In this research, we propose a different scheme from the mentioned methods in terms of the combination of shape information and frequency features of the skin ROI images. The shape information is extracted using invariant moment algorithm to keep the large variability of pornographic images due to pose variations and the DCT is implemented to get the holistic skin information of ROI images which are invariant to scale and rotation.

In this case, the DCT algorithm that is used to extract dominant frequency contents of ROI image (I) having size N, M is presented by the Eq. 1.    (1) where n=1, 2, ··· , N; m=1, 2, ··· , M, and F is Fast Fourier transforms. From the two-dimensional DCT transformation coefficients, holistic skin information is selected from Cb-Cr color space by two processes: convert the DCT transformation coefficients to one-dimensional vector using zigzag rules as implemented in jpeg compression and select first 30 elements from each Cb and Cr vectors.

While the shape information is just extracted from the intensity component of the image because the most information of shape is available in this component. Finally, from both shape and skin information, the compact holistic features (HF) is composed by placing them as a vector as presented in the Algorithm 2. Algorithm 2 The process of holistic features extraction. Input : image (im) and skinTone matrix Output : holistic features (hF) vector Process: sProb ( sum(skin)=(im.rows ( im:cols); if sP rob (0:01 then [Y; Cb; Cr] ( rgb2ycbcr(im); //calculate Invariant Moment iMom ( getInvMoment(Y( skin); //calculate DCT Frequency hfCb ( dct(Cb ( skin); hfCr ( dct(Cr( skin); //Select the most signi?cant values hfCb ( zigzag(hfCb); hfCr ( zigzag(hfCr); hF ( [iMomhfCb(1 : 30) hfCr(1 : 30)]; end if return hF When the compact holistic features are evaluated from 1000 pornographic and 1000 non-pornographic images, it shows good enough discriminant information as distributed in two-dimensional space Fig. 3. The Fig. 3 indicates that the features of pornographic and non-pornographic are separated from one to each other.

It means the compact holistic features are potential to be implemented for recognizing the pornographic image.    Fig. 3 The distribution of HF of 1000 pornographic and 1000 non-pornographic images Multi-Layers Neural Network (MNN) Model There are many types of neural network that can be implemented for pattern recognition which is distinguished by the architecture of neuron, type of training, number of layers, and etc.

Generally, the MNN architecture is shown in Fig. 4 which consist of input vector (p), bias (b), weight matrices (W), and transfer function (f). The weight matrices connecting to inputs vector is called as the input weight (IW), while the weight connecting to outputs layer is called as the layer weights (LW). In addition, superscripts for the various weights indicate the weight of the source (second index) and the destination (first index). From the Fig.

4, the output of the neural network is defined as:
a 3 = f 3 (L W 3,2 f 2 (L W 2,1 f 1 (I W 1,1 p+ b 1 )+ b 2 )+ b 3 )
(2) Fig. 4 The General multi layer Neural Network Model In this research, an MNN model is employed for classification because it can work quickly and powerful. For example, a neural network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function (with a finite number of discontinuities) arbitrarily well.

However, the best variation of the layer and transfer function (how many layers and what the transfer functions are) has to be investigated by performing several experiments. Recognition Process Recognition process consists of training and matching processes. The training dataset consists of pornographic and non-pornographic images. From the dataset, the compact HFs are extracted by Algorithm 2.

Next, features selection are carried out to remove similar features of extracted compact HFs by intersection operation (Eq. 3).
HF P,N = HF P ? HF N - HF P n HF N (3) Where HFP,N is final trained HF, HFP and HFN are compact HFs of pornographic and non-pornographic images, respectively. From these sets, the global mean and standard deviation vectors of each HFP and HFN called as (P, (P and (N, (N are determined, respectively.

Next, in order to obtain the minimum different of mean and standard deviation of both training set, the distance (P, (P and (N, (N are calculated. The HFs having smallest score are concluded as shared information which is removed for getting most discriminant information. Next, the MNN model is trained using the HFP,N which is supervised by two targets vector.

The first target for pornographic HFP is [1 1 1 1 1 1 1 1] and for non-pornographic HFN) is [-1 -1 -1 -1 -1 -1 -1 -1]. For instance, a two-layers neural network with linear, log-sigmoid, and tan-sigmoid transfer functions could achieve the goal of setting error when it was trained using HF (size 64 elements) and defined targets vector. Finally, the classification is performed by simulating the query HF using the obtained MNN.

From the simulation output, if the output vector is close to the first target vector, the query HF is concluded as a pornographic image and otherwise as non-pornographic image. This classification process is supposed to work very fast which is the most benefit of the classification method because the query HF does not need to be compared to all trained HF vectors.

Evaluation and Discussion In order to know the achievement of the proposed method, several experiments were carried out using two datasets called UNRAM[12] and Kia datasets[1]. The UNRAM dataset consists of 687 pornographic and 712 non-pornographic images. While Kia dataset has 18354 images which 9295 and 9059 images are pornographic and non-pornographic, respectively.

The images of both datasets were downloaded from the Internet using some downloader tools. The pornographic images of both datasets have large variability in terms of people, pose, skin. While non-pornographic images contain objects which are similar to the human skin such flower, wood, tiger, dessert, and etc.

The data treatment for the experiments was performed as follows: For each dataset, 50% of pornographic and non-pornographic images were randomly selected as the training set, and their remaining were used as testing. The accuracy, false negative rate (FNR), and false positive rate (FPR) parameters were used for performance indicators (using Eq.

(4, 5, and 6)), and The evaluation was carried out on pc with specification Intel Core i3-2370M, 2.4 GHz, 8 GB RAM. The performance indicators were determined by the formulas that were derived from the confusion table[14], [18] (see Table 1 ):
$\text{Accuracy}(\%) = \frac{TP + TN}{NP + NN} \times 100$ (4)
$\text{FNR}(\%) = \frac{FN}{NP} \times 100$ (5) $\text{FPR}(\%) = \frac{FP}{NN} \times 100$ (6) where NP is total of pornographic testing images, and NN is total of non-pornographic testing images.

Table 1 Confusion value
Actual Value

Porn
Non-Porn

Prediction Outcome
Porn
True Positive (TP): porn images that were correctly classified as porn
False Positive (FP): non-porn that were incorrectly labeled as porn

Non-Porn
False Negative (FN): porn images that were incorrectly marked as non-porn
True Negative (TN):non-porn images that were correctly classified as non-porn

The first experiment was carried out on UNRAM dataset to prove that the proposed compact HF can be used to discriminate between pornographic and non-pornographic images.

In addition, this experiment also investigated what size of HF was sufficient for pornographic image recognition. The matching process in the first experiment was performed by Euclidean distance and the smallest distance was concluded as the best likeness. The experimental results show that the proposed compact HF which consists of shape and dominant skin information gives high enough accuracy, as shown in Fig. 5.

These experimental results prove that the compact HF can be used to discriminate between the pornographic and non-pornographic images. It can be achieved because the compact HF has good enough discriminant information, as shown in Fig. 3. In addition, the best HF size for performing pornographic recognition is 40 elements which are shown by the highest accuracy and small enough FPR and FNR (see Fig.

5.). In detail, the best accuracy is by about 88.17% and the FNR and FPR by about 5.51% and 17.79% respectively. These experimental result also prove that the HF requires small memory space for representing the pornographic image which implies to the computational cost of the recognition process. For further evaluation, the next experiments will be performed by the best size of HF (40 elements). Fig.

5 The effect of HF size on accuracy of the proposed pornographic image recognition methods The second and third experiments were performed to find

the best MNN model parameters (hidden layers and transfer functions) for compact HF classification. In these experiments, the variation of hidden layers and transfer functions were investigated to obtain their best combination of MNN model for classification.

The second experimental results show that the best performance is given by the MNN model having 2 hidden layers (2 HLs), which is indicated by the highest accuracy and the smallest FNR and FPR, as presented in Fig. 6. These achievements agree to the theory of MNN that it can approximate any function (with a finite number of discontinuities) arbitrarily well.

It means the MNN can provide crisp classification hyperplane for pornographic image recognition.   Fig. 6 The performance of pornographic recognition in some MNN models Next, in order to find the best variation of transfer functions for the MNN model having 2 HLs, the third experiment was performed using the same dataset as carried out in the second experiment.

The transfers functions that were evaluated in this experiment were linear (L), log-sigmoid (S), and tan-sigmoid (T). The experimental results show that the best variation transfer functions are T, S, and L, as shown in Fig. 7. It means that the best parameters of MNN model for classifying the compact HF are two HLs and TSL transfer functions.

In addition, the third experimental results also support the second experimental achievement in term of the powerfulness of MNN for classifying the compact HF of pornographic and non-pornographic images.   Fig. 7 The transfer functions variations versus recognition achievements In order to compare the performance of the combination between compact HF and MNN (HF+MNN) for pornographic image recognition to the existing methods (skin probability (SP), skin region (SR), fusion descriptor (FD on YCbCr), and eigenporn on HSV ROI (Ep on HSV) methods[2], [3], [8], [9], [13]), the fourth experiment was carried out on UNRAM dataset using the best size HF and the best MNN model from the previous experiments.

The experimental results show that HF+MNN provides higher accuracy and less FPR than those of existing methods, as shown in Fig. 8. In detail, the HF+MNN method increases the accuracy by about 4.32% and decreases FPR by about 14.65%. However, its FNR increases by about 6.31% of that of the best existing method (FD on YCbCr[3]).

Even though the FNR of HF+MNN is higher than that of the FD method but FNR's increment is much less than FPR's decrement. FPR. Therefore, it can be concluded that HF+MNN outperforms among existing methods. Overall, these experimental results are in-line with all previous achievements which the compact HF of skin ROIs images can be implemented to discriminate the pornographic and non-pornographic images.

This performance can be achieved because the compact HF consist most significant shape and dominant skin information of skin ROI images    Fig. 8 The performance comparison to the some existing methods for UNRAM dataset The next experiment was performed on the large size dataset (Kia dataset[1]) to know the robust performance of the HF+MNN method over large variability pornographic images.

In this case, the HF+MNN method is compared to the latest existing method (MP+NF[1]). The experimental result shows that the HF+MNN provides similar performance to the latest existing method (almost 90% of accuracy, 10% and 7% of FNR and FPR, respectively), as presented in Fig. 1. It re-proves that the combination of compact HF and MNN gives good enough achievement for recognizing pornographic images.

The false classification is caused by the large variability of images due to clothes variations such as the people dress in transparent and mini clothes. In addition, the false recognition also happened due to dressing in skin-like clothes.    Fig. 9 The performance comparison to the recent methods for Kia dataset In order to know, whether the proposed recognition system can work fast the last experiment was carried out. The experimental result shows that the HF+MNN method requires much shorter recognition time by about 0.021 seconds per image than that of existing methods, which is the fastest recognition process (see Fig. 10).

It can be achieved because the compact HF have small size (40 elements) for each image. However, weakness of HF+MNN is the training time by about 194.52 seconds for UNRAM dataset. Long training time is contributed by MNN which is well known as the main weakness of the neural network. In practice, this problem can be handled by separating the training and recognition processes.

From these achievements, HF+MNN method is potential to be implemented for pornographic rejection system for a mobile platform.    Fig. 10 The proposed method computational time compared to that of existing methods Conclusion and Future Works The proposed compact HF which consists of shape and dominant skin information is powerful features for discriminating against pornographic images.

The combination of compact HF and MNN (HF+MNN) has been proven to provide good performances for pornographic image recognition. It means this method is potential to be developed for real-time rejection of pornographic images. The HF+MNN method also can improve the best existing method (FD) that is shown by increasing its accuracy by about 4.32% and decreasing its FPR by about 14.65%, respectively.

In addition, the HF+MNN method gives similar robust performance over large size dataset to the recent existing method (MP+NF) by about almost 90% of accuracy, 10% and 7% of FNR and FPR, respectively. However, our proposed method needs very short recognition time by about 0.021 seconds per images. It means our proposed method can work very fast which is potential to be applied for blocking pornographic image in a smart mobile media.

The results need to be improved by genital and edge information to improve the performances. In addition, in order to know the robustness of the proposed method, it also must be tested by considering the context information of the image. Acknowledgments This research is funded by The Ministry of Research, Technology, and Higher Education under scheme applied research.

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