Proceedings of the Fifth IIEEJ International Workshop
on Image Electronics and Visual Computing 2017
Da Nang, Vietnam, February 28- March 3, 2017

PORNOGRAPHIC IMAGE RECOGNITION USING COMPACT HOLISTIC FEATURES OF SKIN ROI IMAGES AND MULTI-LAYER NEURAL NETWORK

I Gede Pasek Suta Wijaya†, IBK Widiartha†
†Informatics Engineering Dept., Mataram University,
Jl. Majapahit 62, Mataram-Lombok, Indonesia

Keiichi Uchimura††, Gou Koutaki††
††Electrical Engineering and Computer Science Dept., Kumamoto University,
Kurokami 2-39-1, Kumamoto Shi, Japan

ABSTRACT

The paper presents an alternative pornographic image recognition using compact holistic features and multi-layer neural network (MNN). The compact holistic feature of pornographic image, which is pose and scale invariant information, is extracted by shape and frequency analysis of skin region of interests (ROIs) of pornographic image. Main aim of this research is to design pornographic recognition scheme which 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)). The experimental result shows that the HF+MNN provides similar performances to latest existing methods (almost 90% of accuracy, 10% and 7% of FNR and FPR, respectively). However, the HF+MNN method needs very short recognition time by about 0.021 second per image for both tested datasets which is its main benefit.

1. 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 to children and teenagers. A report in 2005 mentioned that 25% of queries in search engines, 8% of emails, and 12% of homepages related to pornographic contents[1]. Regarding to negative effects of pornographic, 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 negative effects of pornographic contents.

Therefore, blocking system which can reject of accessing pornographic contents is needed to decrease negative effects of pornographic contents. In order to build strong blocking system of pornographic contents, good recognition algorithm is needed. In this case, the recognition algorithm determines similarity between input image feature and training set features. If a input image is matched (recognized) as pornographic content, it will be blocked to be viewed or displayed. In order to contribute on rejection pornographic contents, an alternative pornographic image recognition using compact holistic features and neural network is presented. The compact holistic feature of pornographic image, which is pose and scale invariant information, is extracted by shape and frequency analysis of skin region of interests (ROIs) of pornographic image. The skin ROI has been proved that it can handle large variability of pornographic images due to background variations[2, 3, 4]. The main aim of this paper is to design a new scenario of pornographic recognition using compact holistic features that is represented by shape and dominant skin information which can improve performances of existing methods (i.e. skin probability, eigenporn, Multilayer-Perceptron and Neuro-Fuzzy based methods).

2. PREVIOUS WORKS

The state of art approaches to adult/pornographic image recognition has well be presented by Ref. [5], which divided their approaches into three main groups: color, shape and local descriptor based methods. While Ref. [1] also have grouped approaches of 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, 3, 4, 6, 7, 8, 9, 10]. Regarding to texts content based method, materials were classified as pornographic by using probability/entropy of texts associated to pornographic such as 'sex', 'anal', 'xxx', etc. However, this

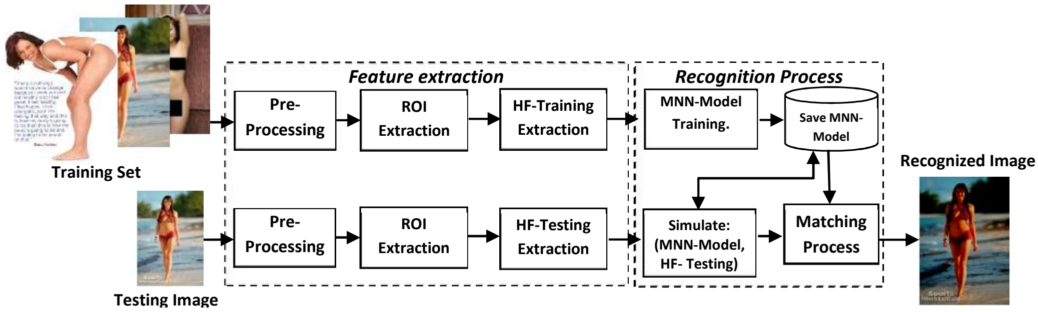


Figure 1: Diagram block of the proposed pornographic image recognition.

method fails to block materials having many pornographic images and videos. Next, a website url based method rejects accessing of adult image using internet firewall such as squid that has rule to block the website addresses (urls) list belonging to pornographic contents. However, adult websites grow quickly and website addresses can easily be renamed by their owners. Finally, a method that is based on image analysis performs rejection of accessing websites based on images or videos that existing in the media. This approach is able to solve weakness of two former methods. As mentioned early, last type of filtering method faces many obstacles because of 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[6], human skin probability[2, 8, 11], and scalable color, edge histogram, and shape descriptors[12]. 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 the FPR and FNR due to large variability of pornographic images. Mostly, skin models that were implemented for segmenting skin region were threshold-based model in the YCbCr, HSV, and RGB color spaces[2, 11] and Gaussian mixture models[6]. Regarding to feature extraction techniques, they can be grouped into holistic, shape, and local (eyes, nose, and mouth, genital) features extraction techniques. All feature extraction techniques are widely used because they can work quickly. The examples of the holistic feature extraction techniques are content-based feature extraction using frequency analysis (FFT, DCT, and Wavelet) [13], eigenporn of the HSV or YCbCr ROI feature extraction [3, 4, 9], and descriptors of color, edge, and shape of pornographic images[12]. The pornographic recognition based on eigenporn of simplified LDA (EP_SLDA), and skin and eigenporn of PCA on YCbCr ROI have been reported that they could provide better performance than that of using fusion descriptor (FD)[3, 4].

The diversity of difference approaches to pornographic recognition show that pornographic image recognition is difficult task due to large variability of images. It also means that pornographic image recognition still challenges research topic. Therefore, alternative solution of pornographic recognition problem using compact holistic features representing shape and dominant skin information and multi-layer neural network (MNN) is proposed to improve our previous works[3, 4] and established methods[1].

3. PORNOGRAPHIC IMAGE RECOGNITION

The diagram block of our proposed pornographic recognition is presented in Fig. 1. The main concern on this research is to design the compact holistic features which consists 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 phonographic images. The classification process is performed using MNN. The main difference of this method to previous works[3, 4] and MP+NF[1] is placed on the features extraction and classification algorithms.

3.1. FEATURES EXTRACTION

The compact holistic features consisting of shape and dominant skin information are presented by vectors that represent global information of pornographic or non-pornographic images. In this case, the compact holistic features, which are design for limited memory space requirement, are extracted from chrominance components (Cb and Cr) of input images. The intensity component (Y) are not included in the features because it is very sensitive to lighting variations. Briefly, the features extraction starts from pre-processing, ROI extraction, and shape and frequency analysis.

3.1.1. Pre-Processing and ROI extraction

A pre-processing process relates to image resizing and lighting normalization. In this case, input image width is scaled into size 256 pixels with keeping aspect ratio to decrease computational time of next processes. The lighting normalization is employed by histogram equalization to handle large variability of input images due to lighting variations. By using normalization, skin pixels that have much lighting effect are successfully classified as skin tone.

Next, 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, 11, 14]. Among those existing methods, the best performance was provided by pixels based skin classification on YCbCr color space[3, 4, 11]. 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:
$skinTone(im.rows, im.cols)$
$r \leftarrow 0, g \leftarrow 0, b \leftarrow 0, i \leftarrow 0, i \leftarrow 0$
for $i = 0; i < im.rows, i++$ **do**
  for $j = 0; j < im.cols, j++$ **do**
    $b \leftarrow im(i,j,1), g \leftarrow im(i,j,2), r \leftarrow im(i,j,3);$
    $intcb \leftarrow int((-0.1481 * r - 0.2908 * g + 0.4390 * b) + 128.0);$
    $intcr \leftarrow int((0.4391 * r - 0.3667 * g - 0.0714 * b) + 128.0);$
    if $(cb >= 80 \&\& cb <= 120) \&\& (cr >= 133 \&\& cr <= 173)$ **then**
      $skinTone(i,j) \leftarrow 1;$
    else
      $skinTone(i,j) \leftarrow 0;$
    end if
  end for
end for
return $skinTone;$

In this case, the *R*, *G*, *B* values are [0,255] while the *Cb* and *Cr* have 225 levels (16-240). These levels are extracted by the RGB to YCbCr transformation algorithm[11]. In addition, morphological is also included on this process to remove false positive skin classification. Output example of skin tone extraction algorithm is shown in Fig. 2.

From the skin tone image, ROI is extracted by the diagram block as shown in Fig. 3. After obtaining skin tone, ROI extraction is started from performing vertical (rows) and horizontal (column) integral projection to know coordinates having large of skin and non-skin region using the Eq. (1) and (2). Secondly, the vertical and horizontal projection probability having less than 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 x and y coordinates where the vertical and horizontal projection probability are thresholded. Finally, the cropped skin tone is mapped on original image to get skin ROI image.

Figure 2: The output example of skin tone extraction.

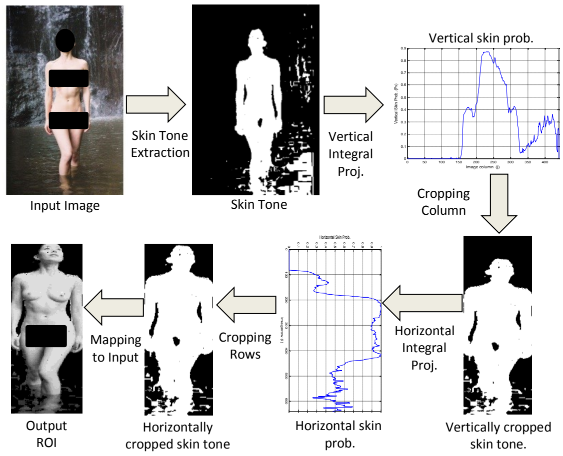


Figure 3: Diagram block of ROI extraction[4].

$$P_h(i) = \frac{1}{H}\sum_{j=0}^{H-1} I(i,j) \quad (1)$$

$$P_v(j) = \frac{1}{W}\sum_{i=0}^{W-1} I(i,j) \quad (2)$$

where *I* is given image having width (*W*) and height (*H*).

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.

3.1.2. Shape and Frequency Analysis

Frequency analysis has been implemented to extract holistic features of an image such as fast Fourier transform[1] and Discrete Cosine Transforms (DCT)[13, 15]. In this research, we propose different scheme from the mentioned methods in terms of combination of shape information and frequency features of the skin ROI images. The shape information is extracted by using hu-moment analysis[16] to handle large variability of pornographic images due to pose variations problem and the DCT is implemented to get holistic skin information of ROI images which are invariant to scale and rotation. In this case, the DCT algorithm that is employed to extract dominant frequency contents of ROI image (I) having size *N*, *M* is presented by the Eq. (3).

$$y = Re\left[e^{-jm\pi/2M} F\left(Re\left[e^{-jn\pi/2N} F(I)\right]_n\right)\right]_m \quad (3)$$

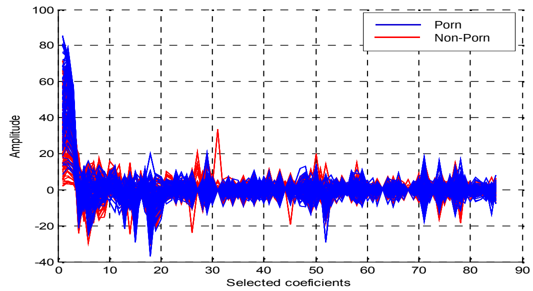
where $n = 1, 2, \ldots, N$, $m = 1, 2, \ldots, M$, and F is Fast Fourier transforms.

Algorithm 2 The process of holistic features extraction.

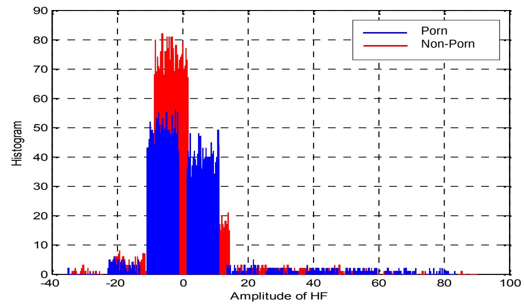
Input : image (im) and skinTone matrix
Output : holistic features (hF) vector
Process:
$sProb \leftarrow sum(skin)/(im.rows * im.cols);$
if $sProb \geq 0.01$ **then**
  $[Y, Cb, Cr] \leftarrow rgb2ycbcr(im);$
  //calculate Invariant Moment (*iMom*)
  $iMom \leftarrow getInvMoment(Y * skin);$
  //calculate DCT Frequency (*hfCb* and *hfCr*)
  $hfCb \leftarrow dct(Cb * skin);$
  $hfCr \leftarrow dct(Cr * skin);$
  //Select the most significant values
  $hfCb \leftarrow zigzag(hfCb);$
  $hfCr \leftarrow zigzag(hfCr);$
  //construct *iMom*, *hfCb* and *hfCr* into hF vector
  $hF \leftarrow [iMom \quad hfCb(1:30) \quad hfCr(1:30)];$
end if
return hF

From two dimensional DCT transformation coefficients, holistic skin information are selected from Cb-Cr color space by two processes: convert the DCT transformation coefficients to one dimensional vector using zigzag rules as done by jpeg compression and select first 30 elements from each Cb and Cr vectors ($hfCb(1:30) \quad hfCr(1:30)]$). While, the shape information is just extracted on intensity component of image because it contains the most shape information. Finally, from both shape and skin information, the compact holistic features (HF) is composed by placing them as a vector as presented in Algorithm 2.

When the HFs are evaluated from 1000 pornographic and 1000 non-pornographic images, it shows good enough discriminant information as distributed in two dimensional space Fig. 4. The Fig. 4 indicates that the HFs of pornographic and non-pornographic are separated from one to each others. It means, the HFs are potentially to be implemented for recognizing pornographic image.



(a) compact holistic features (HF)



(b) histogram of HF

Figure 4: The distribution of HFs of 1000 pornographic and 1000 non-pornographic images

3.2. MULTI-LAYERS NEURAL NETWORK (MNN) MODEL

There are many type of neural network than can be implemented for pattern recognition which are distinguished by architecture of neuron, type of training, number of layer, and etc. Generally, the MNN architecture is shown in Fig. 5 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 input weight (IW), while the weight connecting to outputs layer is called as layer weights (LW). In addition, superscripts for various weights indicate the weight of the source (second index) and the destination (first index).

From Fig. 5, output of neural network is defined by Eq. (4).

$$Y = f^3(LW^{3,2} f^2(LW^{2,1} f^1(IW^{1,1} p + b^1) + b^2) + b^3) \quad (4)$$

In this research, the MNN model is employed for classification because it can works 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 layer and transfer function (how many layers and what the transfer functions are) has to be investigated by performing several experiments.

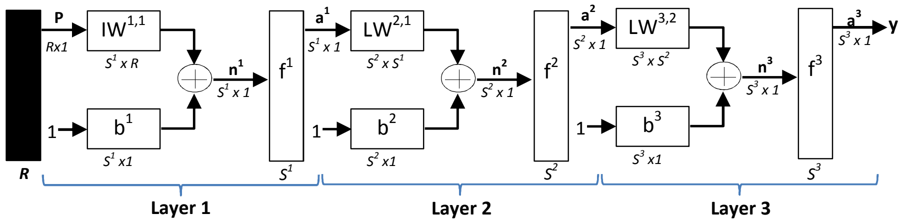


Figure 5: The General multi layer Neural Network Model.

3.3. 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 redundant/shared information by using intersection operation (Eq. (5)).

$$HF_{P,N} = (HF_P \cup HF_N) - (HF_P \cap HF_N) \qquad (5)$$

Where $HF_{P,N}$ is final trained HF, HF_P and HF_N are compact HFs of pornographic and non-pornographic images, respectively. From these sets, global mean and standard deviation vectors of each HF_P and HF_N called as μ_P, σ_P and μ_N, σ_N are determined, respectively. Next, in order to obtain the minimum different of mean and standard deviation of both training set, the distance between μ_P, σ_P and μ_N, σ_N are calculated. The HFs having smallest score are concluded as shared information which are removed for getting most discriminant information.

Next, the MNN model is trained using the $HF_{P,N}$ which is supervised by two targets vector. The first target for pornographic (HF_P) is $[1\,1\,1\,1\,1\,1\,1\,1]$ and for non-pornographic (HF_N) is $[-1 -1 -1 -1 -1 -1 -1 -1]$. For instance, two-layers neural network with linear, log-sigmoid, and tan-sigmoid transfer functions could achieve the goal of setting error when it was trained by using HF (size 64 elements) and defined targets vector.

Finally, classification is performed by simulating query HF using the obtained MNN. From the simulation output, if the simulation output vector is close to the first target vector, the query HF is concluded as pornographic image and otherwise as non-pornographic. This classification process requires very short computational time which is most benefit approach, because the query HF does not need to be compared with all trained HF vectors.

4. EVALUATION AND DISCUSSION

In order to know achievement of the proposed method, several experiments were carried out using two datasets called as UNRAM[4] and Kia datasets[1]. The UNRAM dataset consists of 687 pornographic and 712 images 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 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 human skin such flower, wood, tiger, dessert, and etc. The data treatment for the experiments were performed as follows:

- For each dataset, 50% of pornographic and non-pornographic images were randomly selected as 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, and
- The evaluation was carried out on pc with specification Intel Core i3-2370M, 2.4 GHz, 8 GB RAM.

The performance indicators were derived from confusion table[4].

The first experiment was carried out on UNRAM dataset to prove that the compact HF can be used to discriminate 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 compact HF which consists of shape and dominant skin information gives high enough accuracy, as shown in Fig. 6. These experimental results prove that the compact HF can be used to discriminate pornographic and non-pornographic images. It can be achieved because the compact HF has good enough discriminant information, as shown in Fig. 4. In addition, the best HF size for performing pornographic recognition is 40 elements which is shown by the highest accuracy and small enough FPR and FNR (see Fig. 6). In detail, the best accuracy is by about 88.17% and the FNR and FPR by

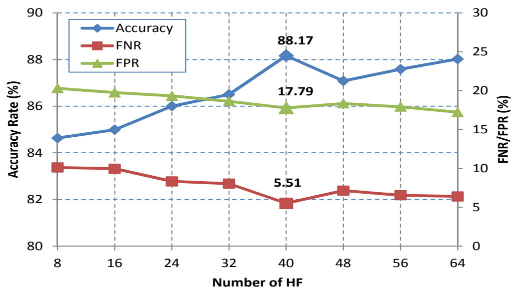


Figure 6: The number of HF versus performance of recognition

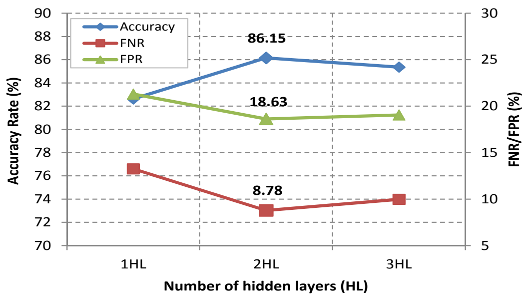


Figure 7: The performance of pornographic recognition in some MNN models

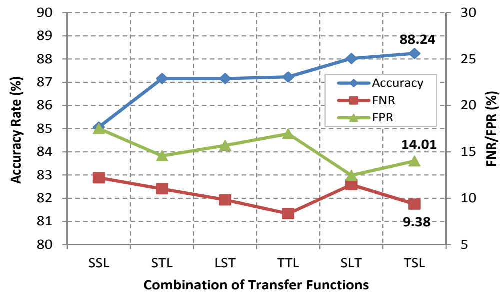


Figure 8: The transfer functions variations versus recognition achievements

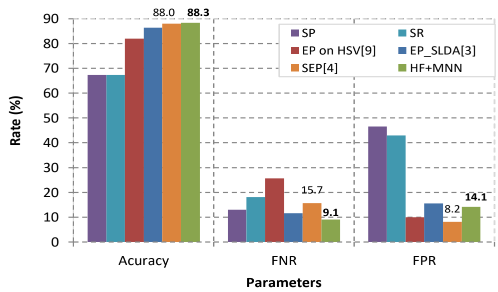


Figure 9: The performance comparison to the some existing methods for UNRAM dataset

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 computational cost of the recognition process. For further evaluation, the next experiments will be performed by the best size of HF (40 elements).

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. 7. These achievements are in-line to theory of the 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.

Next, in order to find the best variation of transfer functions for the MNN model having two hidden layers, the third experiment was performed by using the same dataset as carried out on 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 is T, S, and L, as shown in Fig. 8. It means that the best parameters of the MNN model for classifying the compact HF is two hidden layers and TSL transfer functions. In addition, the third experimental results also support the second achievements in term of powerfulness of the MNN for classifying the compact HF of pornographic and non-pornographic images.

In order to compare performance of the proposed pornographic image recognition (the HF+MNN) to existing methods (skin probability (SP), skin region (SR), eigenporn of SLDA (EP_SLDA) on YCbCr, skin prob and eigenporn on YCbCr (SEP), and eigenporn on HSV ROI (Ep on HSV) methods[2, 3, 4, 6, 9, 11]), the fourth experiment was carried out on UNRAM dataset using the best size HF and the best MNN model from the previous experiments. Experimental results show that overall the HF+MNN provides higher accuracy and less FPR than those of existing methods, as shown in Fig. 9. In addition,the Fig. 9 also shows that HF+MNN provides similar achievements (Accuracy, FNR, and FPR) as the recent method (SEP)[4]. However, the HF+MNN gives much shorter recognition time by about 0.021 second per image than that of SEP method, 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. Overall, these experimental results are in-line with all previous achievements which the compact HF of skin ROIs images can be implemented to dis-

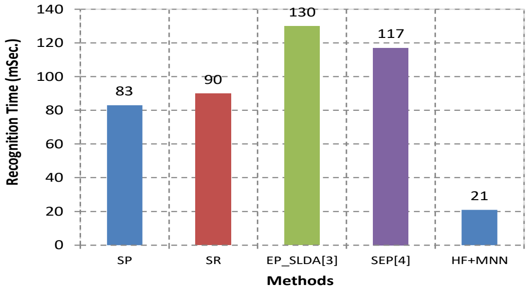


Figure 10: The proposed method computational time compared to that of existing methods

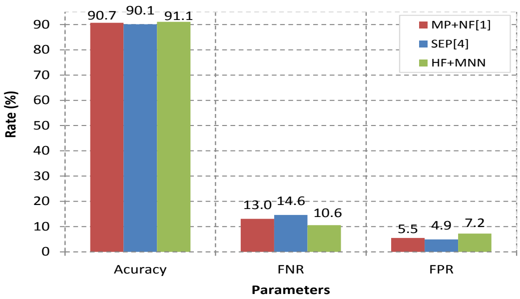


Figure 11: The performance comparison to the recent methods on Kia dataset

criminate the pornographic and non-pornographic images. This performance can be achieved because the compact HF consists most significant shape and dominant skin information of skin ROI images. However, main weakness of the HF+MNN is on the training time by about 194.52 seconds for UNRAM dataset. Its Long training time is contributed by the MNN which is well known as main problem of neural network. In practical, this can be handled by separating the training and recognition processes. From these achievements, the HF+MNN method is potentially to be implemented for real time pornographic rejection system.

The last 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 methods (MP+NF[1] and SEP[4]). The experimental result shows that the HF+MNN provides similar performance to latest existing methods (almost 90% of accuracy, 10% and 7% of FNR and FPR, respectively), as presented in Fig. 10. From specificity and precision point of view, the HF+MNN can decrease the false negative data of both MP+NF and SEP which are shown by increment of specificity (true positive rate) by about 2.44% and 4,02%, respectively, but precision of the HF+MNN decreases less than 2%, as shown in Fig. 11. It means that the HF+MNN gives similar performance as both recent method (MP+NF and SEP). In addition, these experimental results re-prove that the combination between 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, as shown in Fig. 13. The images (Fig. 13(a,b)) were recognized as non-pornographic images because ROI detection did not work due to skin-like backgrounds. While the images (Fig. 13(c,d)) were recognized as pornographic images because the people were dressed by skin-like clothes.

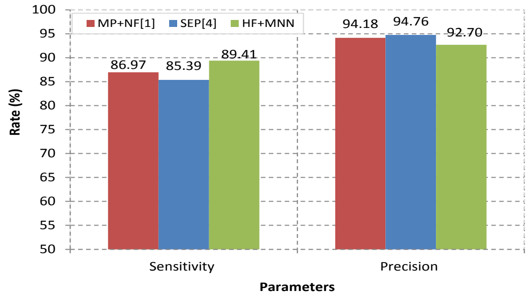


Figure 12: The sensitivity and precision of the HF+MNN compared to both recent methods (MP+NF and SEP) for Kia dataset

Figure 13: The example of false negative (a,b) and positive (c,d) of HF+MNN pornographic image recognition.

5. CONCLUSION AND FUTURE WORKS

The proposed compact HF which consists of shape and dominant skin information is powerful features for discriminating pornographic images. The combination between compact HF and MNN (HF+MNN) has been proved to provide good performances for pornographic image recognition. It means this method is potentially to be developed for real time rejection of pornographic images. In addition, the HF+MNN method gives similar robust performance over large size dataset to recent existing methods (the MP+NF and SEP) by about almost 90% of accuracy, 10% and 7% of the FNR and FPR, respectively. However, our method needs very short recognition time by about 0.021 second.

This method needs to be improved by using genital and edge information to increase the performances. In addition, to know robustness of this method, it must be tested by considering context information of input image.

6. ACKNOWLEDGMENTS

We would like to send my great thank to Image Media Laboratory of Kumamoto University, which provides hardware and software supports to this research. In addition, our great thank is to Japan Students Services Organization (JASSO) for supporting to my research in GSST Kumamoto University.

7. REFERENCES

[1] S. M. Kia, H. Rahmani, R. Mortezaei, M. E. Moghaddam, and A. Namazi, "A novel scheme for intelligent recognition of pornographic images," in *Computer Vision and Pattern Recognition, Cornell University Library*, February 2014. [Online]. Available: http://arxiv.org/abs/1402.5792

[2] J. A. Marcial-Basilio, G. Aguilar-Torres, G. Snchez-Prez, L. K. Toscano-Medina, and H. M. Prez-Meana, "Detection of pornographic digital images," *International Journal of Computers*, vol. 5, no. 2, pp. 298–305, 2011.

[3] I. G. P. S. Wijaya, I. B. K. Widiartha, K. Uchimura, and G. Koutaki, "Pornographic image rejection using eigenporn of simplified lda of skin rois images," in *2015 International Conference on Quality in Research (QiR)*, Aug 2015, pp. 77–80.

[4] I. G. P. S. Wijaya, I. Widiartha, and S. E. Arjarwani, "Pornographic image recognition based on skin probability and eigenporn of skin rois images," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 13, no. 3, pp. 985–995, 2015.

[5] C. Ries and R. Lienhart, "A survey on visual adult image recognition," *Multimedia Tools and Applications*, vol. 69, no. 3, pp. 661–688, 2014. [Online]. Available: http://dx.doi.org/10.1007/s11042-012-1132-y

[6] W. Hu, O. Wu, Z. Chen, Z. Fu, and S. Maybank, "Recognition of pornographic web pages by classifying texts and images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 6, pp. 1019–1034, 2007.

[7] L.-H. Lee and C.-J. Luh, "Generation of pornographic blacklist and its incremental update using an inverse chi-square based method," *Information Processing & Management*, vol. 44, no. 5, pp. 1698 – 1706, 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306457308000514

[8] R. Mustafa and D. Zhu, "Objectionable image detection in cloud computing paradigm-a review," *Journal of Computer Science*, vol. 9, no. 12, pp. 1715–1721, 2013.

[9] I. G. P. S. Wijaya, K. Uchimura, and G. Koutaki, "Pornographic image recognition using eigenporn of hsv skin segmented image," in *Proceeding of the 2015 IEICE General Conference*, Kyoto, Japan, March 2015.

[10] A. Zaidan, N. Ahmad, H. A. Karim, M. Larbani, B. Zaidan, and A. Sali, "On the multi-agent learning neural and bayesian methods in skin detector and pornography classifier: An automated anti-pornography system," *Neurocomputing*, vol. 131, pp. 397 – 418, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925231213009326

[11] J. A. M. Basilio, G. A. Torres, G. S. Pérez, L. K. T. Medina, and H. M. P. Meana, "Explicit image detection using ycbcr space color model as skin detection," *Applications of Mathematics and Computer Engineering*, pp. 123–128., 2011.

[12] J.-L. Shih, C.-H. Lee, and C.-S. Yang, "An adult image identification system employing image retrieval technique," *Pattern Recognition Letters*, vol. 28, no. 16, pp. 2367 – 2374, 2007. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167865507002449

[13] W. Chen, M. J. Er, and S. Wu, "Pca and lda in dct domain," *Pattern Recognition Letters*, vol. 26, no. 15, pp. 2474 – 2482, 2005. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167865505001522

[14] Z. Ma and A. Leijon, "Human skin color detection in rgb space with bayesian estimation of beta mixture models," in *Proc. of 18th European Signal Processing Conference (EUSIPCO-2010)*, Aalborg, Denmark, 2010, pp. 1204–1208.

[15] I. G. P. S. Wijaya, K. Uchimura, and G. Koutaki, "Face recognition based on incremental predictive linear discriminant analysis," *IEEJ Transactions on Electronics, Information and Systems*, vol. 133, no. 1, pp. 74–83, 2013.

[16] R. C. Gonzalez and R. E. Woods, *Digital Image Processing (3rd Edition)*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 2006.