Human Body Parts Candidate Segmentation using Laws Texture Energy Measures with Skin Color

Byeongcheol Choi*, Seungwan Han*, and Byungho Chung*, Jaecheol Ryou**

* Information Security Research Division, Electronics and Telecommunications Research Institute, Daejeon, Korea

** Department of Computer Science, Chungnam National University, Daejeon, Korea

{corea, hansw, cbh}@etri.re.kr, jcryou@home.cnu.ac.kr

Abstract— **This paper presents a novel human body parts segmentation method using Laws texture energy measures with skin color in YCbCr. The proposed segmentation is used in the candidate detection phase of human body part recognition. Therefore, this work can be widely applied to face detection, person layout detection, contents filtering, and privacy protection.**

Keywords— **Human Body Parts, Image Segmentation, Laws Texture Energy Measures, Skin Color Detection, YCbCr**

I. INTRODUCTION

Detection and recognition of human body parts provides solution required by the service/content providers in broadcasting TV, cable TV, S(satellite)/ T(terrestrial) DMB (digital multimedia broadcasting), and Internet-based live broadcasting or streaming multimedia services.

Human body parts detection technology is used for data compression for transmission, privacy protection, security and safety surveillance, contents management, and harmful contents filtering for children and young people at home and common sites.

The state-of-the-art of human body detection focuses on face, hand and foot, outlier of person's image. Also, body parts detection is useful for analyzing medical images and naked people images. In this case, regions of interest are the head/face, hand, foot, and other special body parts and we can analyze images using skin color modeling and detection, face detection and recognition, person/people detection in surveillance, and adult image detection.

Digital color image processing is performed in RGB, HSV, YCbCr, CIE-LAB, etc. color spaces. Broadcasting multimedia contents use YCbCr color spaces because it is an orthogonal and linear color space. Y refers to the intensity of illumination channel and CbCr refers to the chrominance channel that has no relationship to illumination. This color space is very useful for transmitting and analyzing broadcasting TV contents.

Skin color modeling uses various skin color models and color spaces. Blob detection is used for grouping pixels of detected skin pixels. The skin color detection by Jones and Rehg uses a statistical skin color model. This is accomplished by estimating the distribution of skin and non-skin color in the color space using labeled training data using mixture of Gaussian model. To detect adult images, some simple features are extracted. The discrimination performance based solely on skin is good for simple features without close-up facial images. The blob detection by Ming and Ma can adapt to both intensity and color of images.

Adult image detection is an application of body parts detection technology and is used for parental control and contents-filtering of CBIR (content-based image retrieval) and MIR (multimedia information retrieval). The SVM-based adult image detection by Rowley, Jing, and Baluja is used for filtering adult images in large scale Internet applications using multiple features and SVM. This method uses skin color factors for SVM modeling. This scheme has been incorporated and deployed into Google's adult content filtering infrastructure for image safe-search. The guidelines of objectionable multimedia contents filtering and degrees are offered in the RSACi, ENC (Electronic Network Consortium) guideline of Japan, and Safenet of Korea, and etc.

A general purpose approach for identifying and processing body candidates are needed to detect human body parts and filter harmful contents. This paper proposes a method for human body parts candidate segmentation. The proposed method uses Laws texture energy measures in Y intensity of illumination channel and skin color blob detection in CbCr chrominance channel.

This paper is organized as follows. Section II gives an overview of human body parts detection technology and cites previous related work. Section II describes digital color spaces. Section III explains Laws texture energy. The proposed scheme is described in Section IV. Experimental results are given in Section V, and the paper is summarized in Section VI.

II. System Overview

This section explains system requirements, system architecture, and performance measures for the proposed system evaluation.

A. System Requirements

The candidate detection of face and personal layout has so far focused on pattern matching based on image scaling and scanning. This work proposes a more elegant solution for human body parts recognition. The requirements of the proposed system are as follows:

- ✓ Use orthogonal color space
- ✓ Solve the noise, illumination, and rotation effects
- ✓ Detect the human body parts candidate

B. System Architecture

YCbCr color space conversion, skin color modeling, blob detection, and Laws texture energy measures for detailed segmentation of human body parts are needed to solve the problems with the previously mentioned requirements. Figure 1 shows the proposed system architecture. The major procedure is as follows:

- ✓ 1st step – Convert RGB input image to YCbCr color space and split the channels
- ✓ 2nd step – Perform skin color blob detection and texture energy blob detection
- ✓ 3rd step – Perform human body parts candidate detection sing convolution skin blobs and texture energy blobs

In this paper, we use Bayesian classification to model skin color and Laws texture energy measures to map texture energy for candidate detection.

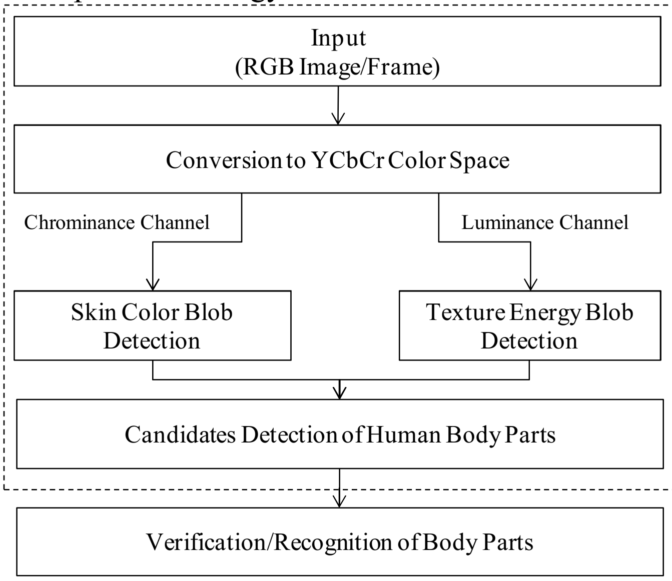


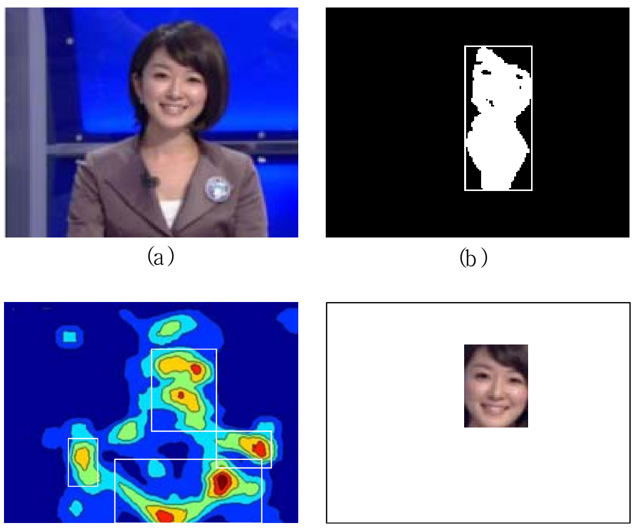
Figure 1. Proposed system architecture

C. Performance Measures

To evaluate the proposed system, three performance measures are used; TDR(True Detection Rate), FDR(False Detection Rate), and MDR(Miss Detection Rate) are defined in Table I.

TABLE 1. Dataset for Training and Testing

Measure	Descriptions
TDR	#(True Detected ROIs) / #(Detected ROIs)
FDR	#(False Detected ROIs) / #(Detected ROIs)
MDR	#(Miss Detected ROIs) / #(Ground Truth ROIs)



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

Figure 2. Processing of human body parts candidates detection (a) original image, (b) after skin color blob detection, (c) after Laws texture energy blob detection, (d) candidate after convolution (b) and (c)

III. PROPOSED SCHEME

In this section, we describe in detail the methods used in the human body parts detection system. Figure 2 shows the human body parts candidate detection - (a) before processing (b) after skin color blob detection, (c) after Laws texture energy blob detection, and (d) after convolution of (b) and (c). This demonstrates that the proposed method performs segmentation procedure well.

A. Digital Color Spaces and YCbCr

Digital color spaces are divided into device-dependant color spaces and device-independent color spaces defined by CIE (International Commission on Illumination) with the consideration of HVS (human visual system).

In this paper, RGB color space is linearly converted to the YCbCr color space. Y Channel is used as the luminance channel to analyze texture energy map and Cb/Cr is used as Chrominance for skin color modeling and detection.

B. Skin Blob Detection in Chrominance Channel

Skin color detection is a key technology for preprocessing face detection and tracking, analyzing gestures, filtering adult contents, performing CBIR (content-based image retrieval), and providing various human computer interaction. Skin color detection uses various core methods such as color spaces, quantization, modeling and classification.

RGB, YCbCr, HSV, and CIE-LAB are generally used in skin color detection. Bayesian classifier, MLP (Multilayer Perceptron), and GMM (Gaussian Mixture Model) are used as classifiers.

In this paper, Bayesian classifier with MAP (maximum a posteriori) is used for skin color detection and flood fill is used for blob detection.

C. Laws Texture Energy Blob Detection in Illumination Channel

Laws texture energy Blob detection is a simple approach for implementing various object detection methods.

Laws 1-D Basic Masks

Laws 1-D Masks consist of a 1x3 and 1x5 matrix. Equation (1) shows 1x5 1-D Masks.

$$\begin{aligned} L5 &= [1,4,6,4,1] \\ E5 &= [-1,-2,0,2,1] \\ S5 &= [-1,0,2,0,-1] \\ W5 &= [-1,2,0,-2,1] \\ R5 &= [1,-4,6,-4,1] \end{aligned} \quad (1)$$

,where L5, E5, S5, W5, R5 1-D masks are for detecting locality or level, edge, spot, wave, and ripple respectively. 1-D Masks are important concepts for 2-D convolution masks.

Laws 2-D Convolution Masks

2-D masks for Laws texture energy measures are generated by convolution of 1-D Mask. Equation (2) is an example of 2-D convolution mask between W5 and E5.

$$W5^T E5 = \begin{bmatrix} -1 \\ 2 \\ 0 \\ -2 \\ 1 \end{bmatrix} \times \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 0 & -2 & -1 \\ -2 & -4 & 0 & 4 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 4 & 0 & -4 & -2 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix} \quad (2)$$

$L5^T L5$ and $R5^*$ / $^*R5$ are not considered in this paper. 15 5x5 Laws 2-D convolution masks are used in the proposed system.

Texture Energy Measures

Texture Energy Measures are defined as (3). Here E is energy and F is a core function for calculating the texture energy. The vertical and horizontal sizes of basic window are both 2w+1 and the value of texture energy can be calculated by convoluting (m, n) pixel of image from -w to w.

$$E_k(m,n) = \sum_{j=n-w}^{n+w} \sum_{i=m-w}^{m+w} |F_k(i,j)| \quad (3)$$

, where $F_k(i, j)$ is given (4).

$$F_k(m,n) = M(m,n) * I(m,n), \ k = 0,...,15 \quad (4)$$

, where $M(m,n)$ is the 5x5 Laws texture energy masks and $I(m,n)$ is the Y (intensity of illumination channel) in YCbCr color space.

Texture energy map is calculated by shift convoluting image with masks with window size of 15x15. 15 texture energy maps are made using 15 5x5 combined masks shown in Figure 3. Here we use two thresholds for detecting candidates: T_{Energy} and $T_{Candidate}$.

Figure 3. Fifteen Laws texture energy maps of original image

IV. Implementation and Experimental Results

In this section, we describe dataset and experimental results of proposed system.

A. Dataset

The proposed system can detect various human body parts. For the performance test, contents were gathered from the internet and divided to various genres. Table II shows test set for the performance evaluation of the proposed system and the test data consist of benign 1000 and adult 1000 set.

TABLE 2. Dataset for Training and Testing

Genre	Sub-genre	Test set
Benign	People (single)	330
	Innerwear [InnerW]	130
	Bikini	440
	People (more than two) [Etc.]	100
Adult	Type I [B]	70
	Type II [Br1]	122
	Type III [Br2]	150
	Type IV [H]	36
	Type V [G]	198
	Type VI [F.E]	290
	Type VII [S.I]	134

B. System Prototype

Matlab was used for algorithm verification and visual c++ and OpenCV for the performance testing. LibSVM and MPEG-7 XM library were also used for supervised verification of body parts models. Figure 4 shows the system prototype of the proposed ROI detection scheme.

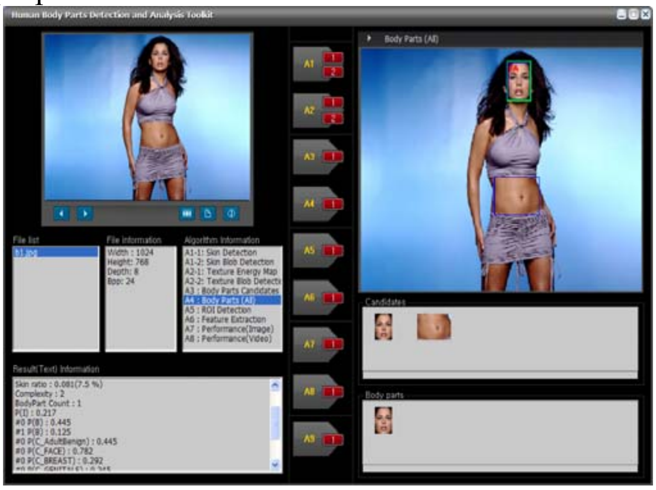


Figure 4. Snapshot of experimental toolkit

C. Experimental Results

TDR (true detection rate), FDR (false detection rate), MDR (miss detection rate) were used for the performance matrix of ROI detection. Face(FA), top or breats(BR) , and genitals(GE) were taken as candidates for candidate segmentation

L5S5 of 15 Laws texture energy was used for performance testing. Figure 5 shows that the proposed system gives TDR of 93.63%, FDR of 10.13%, and MDR of 6.9%.

V. Conclusion

A novel and universal scheme was suggested for ROI detection of various human body parts. The proposed method achieves human body parts candidate segmentation using skin color detection and Law texture energy measures. Performance of the proposed system is TDR of 93.63%, FDR of 10.13%, and MDR of 6.9%.

Acknowledgment

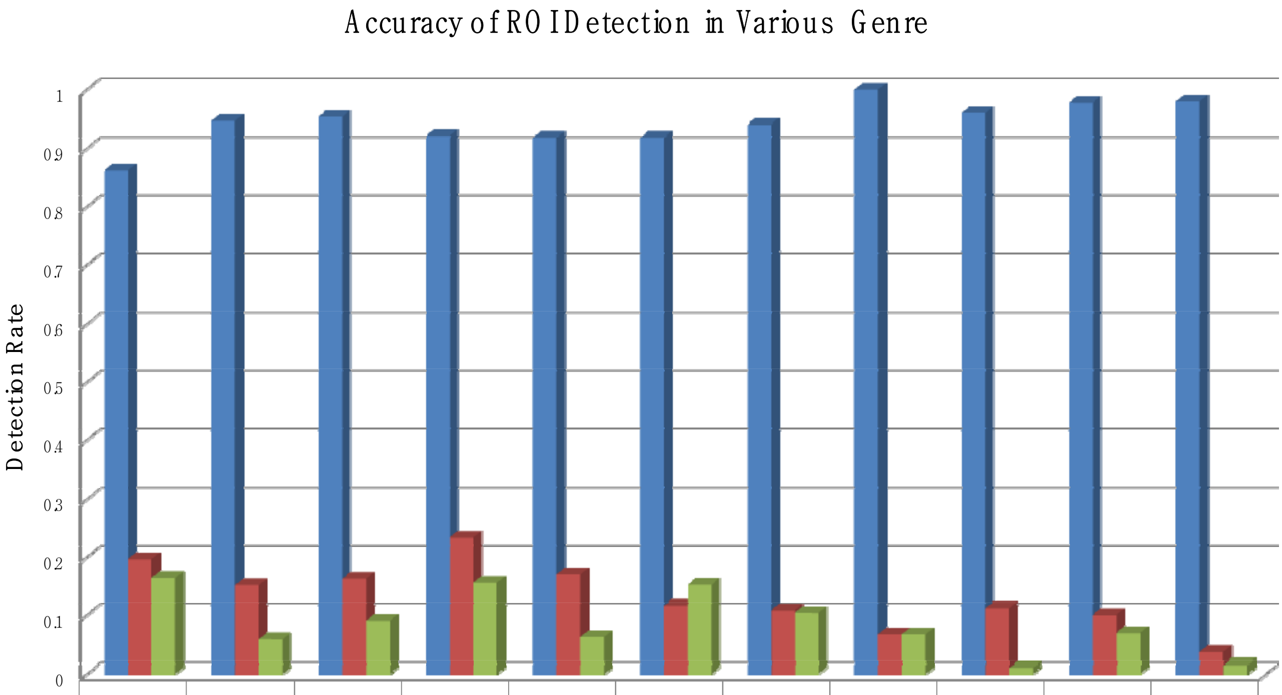
This work was supported by the IT R&D program of MKE/KEIT (KI002069, Development of the Illegal and Objectionable Multimedia Contents Analysis and Filtering Technology).

References

[1] P. Kakumanu, S. Makrogiannis, and N. Bourbakis, “A survey of skin-color modeling and detection methods”, Pattern Recognition 40 pp1106-1122, 2007

[2] Son Lam Phung, Abdesselam Bouzerdoum, and Douglas Chai, “Skin Segmentation Using Color Pixel Classification: Analysis and Comparison”, IEEE Trans. on PAMI, Vol.27, No.1, Janunary 2005

[3] Ying Liua, Dengsheng Zhanga, Guojun Lua, Wei-Ying Mab, “A survey of content-based image retrieval with high-level semantics”, Pattern Recognition 40 pp262-282, 2007
[4] Rastislav Lukac, Bogdan Smolka, Karl Martin, Konstantinos N. Plataniotis, and Anastasios N. Venetsanopoulos, “Vector Filtering for Color Imaging”, IEEE Signal Processing Magazine, January 2005
[5] Ritendra Datta, Dhiraj Joshi, Jia Li, and James Z. Wang, “Image Retrieval: Ideas, Influences, and Trends of the New Age”, ACM Computing Surveys, Vol. 40, No. 2, Article 5, April 2008
[6] Michael S. Lew, Nicu Sebe, Chabane Djeraba, and Ramesh Jain, “Content-Based Multimedia Information Retrieval: State of the Art and Challenges”, ACM Transactions on Multimedia Computing, Communications and Applications, Vol. 2, No. 1, February 2006
[7] M.J. Jones and J.M. Rehg, "Statistical color models with application to skin detection", CVPR, 274-280, 1999
[8] D. Chai and K.N. Ngan, “Face segmentation using skin color map in videophone applications”, IEEE Trans. on CSVT, vol.9, 551-564, 1999
[9] A. F. Abate, M. Nappi, D. Riccio, and G. Sabatino, “2D and 3D face recognition: A survey”, Pattern Recognition Letters 28 (2007)
[10] P. Viola, and M. Jones, “Rapid Object Detection using a Boosted Cascade of Simple Features”, CVPR 2001
[11] A. Ming, and H. Ma, “A blob detector in color images”, ACM International Conference on Image and Video Retrieval, July 2007
[12] Jau-Ling Shih, Chang-Hsing Lee, Chang-Shen Yang, “An Adult Image Identification System Employing Image Retrieval Techniques”, Pattern Recognition Letters 28 pp2367–2374, 2007
[13] Jiann-Shu Leea, Yung-Ming Kuob, Pau-Choo Chungb, E-Liang Chenc, “Naked image detection based on adaptive and extensible skin color model”, Pattern Recognition 40 pp2261–2270, 2007
[14] Weiming Hu, Ou Wu, Zhouyao Chen, Zhouyu Fu, and Steve Maybank, “Recognition of Pornographic Web Pages by Classifying Texts and Images”, IEEE Transactions on PAMI, Vol.29, No.6, June 2007
[15] James Ze Wang, Jia Li, Gio Wiederhold and Oscar Firschein, "System for screening objectionable images", Images and Computer Communications Journal, 1998
[16] Henry A. Rowley, Yushi Jing, and Shumeet Baluja, “Large Scale Image-based Adult Content Filtering”, International Conference on Computer Vision Theory and Applications, 2006
[17] B.C.Choi, J.N.Kim, and J.C.Ryou, “Adult Image Detection with Close-up Face Classification”, IEEE Conference on Consumer Electronics, January 2009
[18] Christopher Richard Wren, Ali Azarbayejani, Trevor Darrell, and Alex Paul Pentland, “Pfinder: Real-Time Tracking of the Human Body”, IEEE Transactions on PAMI, Vol.19, No.7, July 1997
[19] Navneet Dalal and Bill Triggs, “Histograms of Oriented Gradients for Human Detection”, IEEE Computer Society Conference on CVPR 2005
[20] Qiang Zhu, Shai Avidan, Mei-Chen Yeh, and Kwang-Ting Cheng, “Fast Human Detection Using a Cascade of Histograms of Oriented Gradients”, CVPR 2006
[21] Sheng Bia, Baolin Shaob, Dequn Lianga, Xiaoyan Shena, “Human body segmentation based on adaptive feature selection in complex situations”, Proceeding of SPIE, February 2008
[22] K.I.Laws, “Textured image segmentation”, PhD Thesis, University of Southern California
[23] S.Suresh Kumar and L. Ganesan, “Texture Classification using Wavelet based Laws Energy Measures”, International Journal of Soft Computing, pp293-296, 2008
[24] B.S. Manjunath, P. Salembier and T. Sikora, Introduction to MPEG-7: Multimedia Content Description Interface, John Wiley&Sons Ltd., 2002
[25] C.W. Hsu, C.C. Chang and C.J. Lin, “A Practical Guide to Support Vector Classification”, Dec.20, 2007, http://www.csie.ntu.edu.tw/~cjlin
[26] J. Kittler, M. Hatef, R. P.W. Duin, and J. Matas, “On Combining Classifiers”, IEEE Transactions on PAMI, Vol.20, No.3, March 1998
[27] M. Cho, The Basic Principles of Digital Color, Kukje, 2006



	011 People	012 InnerW	013 Bikini	014 Etc	101 B	102 Br1	103 Br2	104 H	105 G	106 FE	107 S.I
TDR	0.862068966	0.946107784	0.953125	0.921568627	0.918918919	0.918918919	0.94	1	0.95959596	0.977142857	0.979591837
FDR	0.196551724	0.151497006	0.1625	0.233333333	0.17027027	0.116216216	0.108	0.066666667	0.112121212	0.1	0.036054422
MDR	0.164	0.058227848	0.090163934	0.155319149	0.062162162	0.152252252	0.104	0.066666667	0.011111111	0.068571429	0.015646259

Figure 5. Experimental results: accuracy of proposed system