An Optimal Chrominance Plane in the RGB Color Space for Skin Color Segmentation

Cheol-Hwon Kim[1], and June-Ho Yi[2]

[1]NextEye Co., Ltd. Shinsegi Plaza 4F 900-9, Pyungchon-dong,
Dongan-gu Anyang, 430-070, Korea
[2]School of Information & Communication Engineering
Sungkyunkwan University 300, Chunchun-dong, Jangan-gu
Suwon, 440-746, Korea

chkim@nexteye.com, jhyi@ece.skku.ac.kr

Abstract

In the case of illumination or pose changes, the distribution of skin colors in color planes is very variant. This makes it hard to employ color histogram based approaches to skin color segmentation. We propose online PCA analysis of skin colors directly in the RGB color space. Our idea is simple but works well. Based on the observation that skin colors of a person in the RGB color space are approximately distributed in a linear fashion, we apply PCA techniques to RGB values of skin colors from a set of training images collected online. The axis along which the data is spread most corresponds to the axis of illumination intensity. We use the remaining two axes to form a chrominance plan in which the distribution of skin colors is invariant. We have preprocessed the input images using a retinex algorithm in order to compare the color constancy property of the proposed plane with the HS and IQ planes. As we expected, the retinex algorithm significantly changed the distribution of skin colors in the HS and IQ planes. The experimental results show that the performance of skin color segmentation using the proposed plane is much more robust to illumination and pose changes compared to those using HS or IQ planes.
Keyword: PCA, Retinex, Skin color segmentation.

I. Introduction

Skin region detection is a very important problem for the realization of vision based human-computer interfaces. The most practical solution to this problem is color segmentation where segmentation is based on the lookup of a learned 2D color histogram [1, 2]. The two axes of the color histogram correspond to the chrominance component of an appropriate 3D color space. Most commonly used color planes for building color histograms are the HS plane of the HIS color space [5] and the IQ plane of the YIQ color space [6].

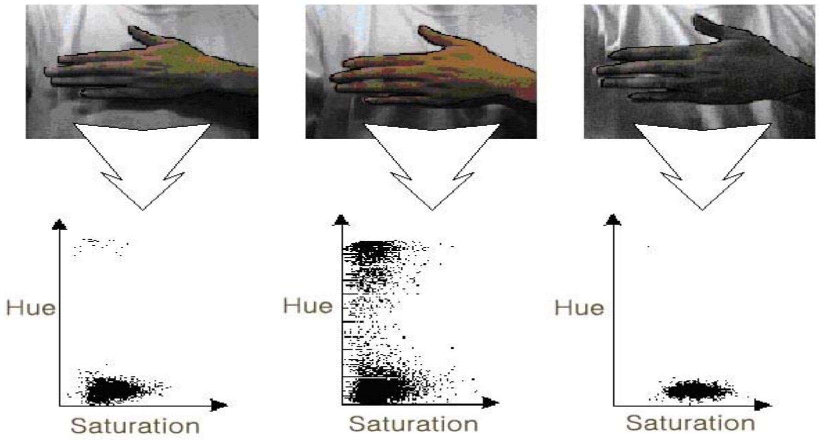


Fig. 1 color histograms based on H and S values of the same skin region under various lighting conditions due to illumination or hand pose changes

In order to achieve good segmentation performance, the distribution of skin colors in a learned color histogram should not be much variant. At the same time, the learned color histogram should contain most skin colors detected in the input images. If a chrominance plane chosen for building the color histogram provides this property, we can make a stable use of the histogram without its update. However, in the case of illumination or pose changes, the distribution of skin colors in the HS or IQ planes is still very variant. Fig. 1 shows examples of color histograms of H (hue) and S (saturation) values of the same skin region under various lighting conditions due to illumination or hand pose changes. The distributions of H and S values of the same skin region are quite different. This makes it very hard to use its color histogram without its update for skin color segmentation [7]. Thus it is quite probable that HS or IQ values of many skin pixels in the input image do not belong to the skin color regions of the learned color histogram. These pixels are classified as non-skin pixels. In most cases, color histograms based on the HS or IQ planes need to be updated in order to give performance robust to illumination changes.

We propose a new chrominance plane of the RGB color space for building color histograms. The chrominance plane is computed by online PCA analysis of skin colors of the current user as can be seen in Fig. 2. By using this plane in the RGB color space, RGB color values of the input image do not need to be converted into HIS or YIQ color coordinates. We have observed an important fact that skin colors in the RGB color space are approximately distributed in a linear fashion [3, 4]. Based on this fact, we have applied PCA techniques to RGB values of skin colors from a set of training images collected online. The axis along which the data is spread most corresponds to the axis of illumination intensity. The other two axes provide a nice chrominance plane for building color histograms. In this plane, the distribution of skin colors is invariant compared to those in the HS or IQ planes. At the same time, a learned color histogram contains most skin colors detected in the input images. We have employed online training of skin colors because segmentation can be more accurate if user-specific skin colors are used.

We have used a retinex algorithm [8, 9] to preprocess the input images in order to see the retinex effect on the distribution of skin colors in the HS, IQ and proposed chrominance plane. A retinex algorithm is a human perception based image processing algorithm that is used for eliminating illumination effects. We have observed that the distribution of skin colors in the HS and IQ is influenced a lot by the retinex algo rithm while almost no effect is made in the proposed plane. This shows the desired property of the proposed chrominance plane in terms of color constancy. We have compared the segmentation performance of the proposed plane with that of HS or IQ planes under varying illumination conditions using a simple lookup table method for skin color segmentation. The experimental results show that our chrominance plane gives good segmentation performance much more robust to illumination or pose changes than the HS and IQ planes.

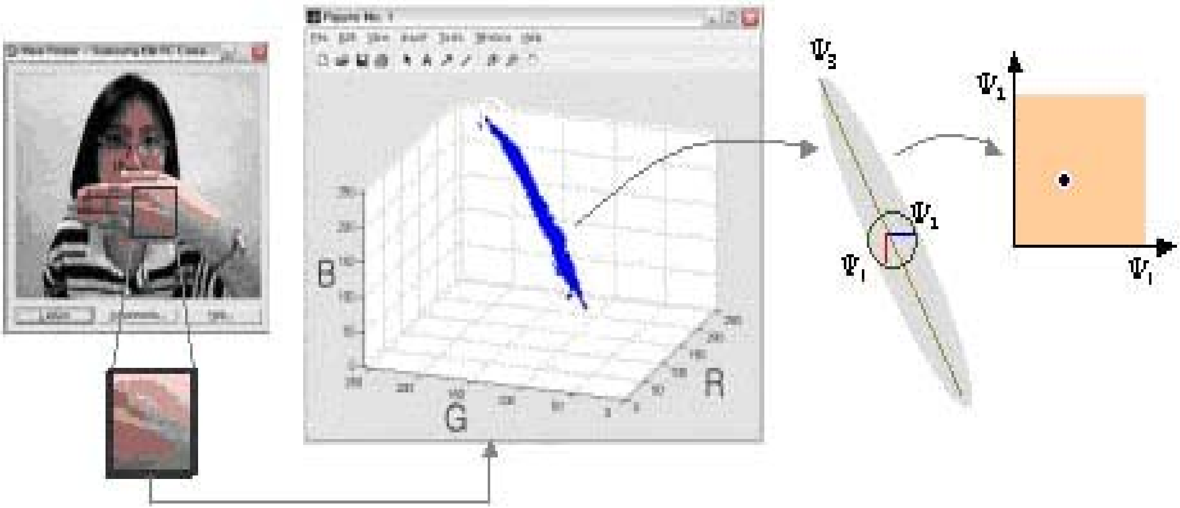


Fig. 2 online PCA analysis of the current user's skin colors in the RGB color space: (a) The skin colors approximately distributed in a linear fashion in the RGB color space. (b) The PCA analysis yields a chrominance plane $(\vec{\psi}_1, \vec{\psi}_2)$ in the RGB color space for building a color histogram.

II. Retinex Algorithm and PCA Analysis

This section gives a brief explanation of the retinex algorithm and PCA techniques used in our method.

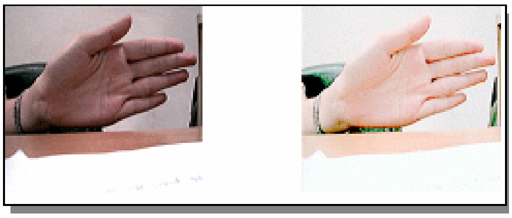
A. Retinex algorithm

Since Edwin Land introduced the theory [10], several variant algorithms [8, 9] have been reported in the literature. In retinex algorithms, an intensity value I_i of *i* th spectral band (*i* = R, G or B) at (x, y) is simply modeled as a product of terms representing reflection and illumination factors.

$$I_i(x, y) = S_i(x, y) r_i(x, y). \tag{1}$$

where $S_i(x, y)$ and $r_i(x, y)$ denote the illumination factor and the scene reflectance factor of *i* th spectral band, respectively. The retinex output in each spectral band is defined as

$$R_i(x, y) = \log \frac{I_i(x, y)}{\bar{I}_i(x, y)} = \log \frac{S_i(x, y) r_i(x, y)}{\bar{S}_i(x, y) \bar{r}_i(x, y)}. \tag{2}$$



(a)

(b)

Fig. 3 two examples illustrating the effect of the retinex algorithm: (a) input images (b) output images after the retinex algorithm is applied. The retinex algorithm has recovered the original colors in the shadowed areas by removing illumination effects.

where $\bar{I}_i(x, y)$ represents spatially weighted average intensity value at (x, y). Assuming slowly varying illumination, i.e., $S_i(x, y) \approx \bar{S}_i(x, y)$, if we take the ratio of the current pixel value over a blurred version of neighboring pixel values, we only end up with a reflectance ratio because the illumination terms are cancelled out. This reflectance ratio dominates illumination variation and represents the origin al colors. $\bar{I}_i(x, y)$ can be calculated by a surround function $M_i(x, y)$ [8]. A surround function, $M_i(x, y)$, is employed to consider illumination variations around a pixel of interest. Thus the regular form of a retinex algorithm can be written as

$$R_i(x, y) = \log I_i(x, y) - \log[M_i(x, y) * I_i(x, y)]. \tag{3}$$

In practice, the same surround function is used for each spectral band. A practical application of a retinex algorithm is to employ a multiscale retinex (MSR) algorithm [9] that takes several surround functions simultaneously. In the case of the *i* th band, the output of the multiscale retinex algorithm R_i^{multi} is

$$R_i^{multi}(x, y) = \sum_{s=1}^{S} w_s (\log[I_i(x, y) - I_i(x, y) * M_s(x, y)). \tag{4}$$

where S is the number of scales used and w_i the weight of the scale. The surround function M_s is usually defined by a Gaussian function as in (5).

$$M_s(x, y) = K \cdot \exp\left[-\frac{(x^2 + y^2)}{\sigma_s^2}\right]. \tag{5}$$

where σ_s is the standard deviation of the s th surround function and K is usually set to 1. The surround function, $M_s(x, y)$, should meet the condition, $\iint M_s dxdy = 1$[14]. This means that the sum of all weights is to be normalized. Fig. 3 illustrates the retinex effect. The illumination effects caused by lighting and pose variations are eliminated in the output images.

B. Principal Component Analysis

Let X be a set of RGB values of pixels that belong to skin regions from a sequence of training images collected online.

$$X = [\vec{X}_1, \vec{X}_2, ..., \vec{X}_T] \tag{6}$$

where T denotes the number of training images. The mean vector, $\vec{M}$, is computed as $\vec{M} = \sum_{i=1}^{T} \vec{X}_i$ and we get the matrix Φ by subtracting $\vec{M}$ from $\vec{X}_i$'s:

$$\Phi = [\vec{\Phi}_1, \vec{\Phi}_2, ..., \vec{\Phi}_T]. \tag{7}$$

where $\Phi_i = \vec{X}_i - \vec{M}_i$. The covariance matrix, S_T, is computed as:

$$S_T = \sum_{i=1}^{T} \vec{\Phi}_i \vec{\Phi}_i^T = \Phi\Phi^T. \tag{8}$$

The eigenvalues and eigenvectors of S_T are obtained using the following equation:

$$\mathrm{S}_T \Psi = \Psi\Lambda. \tag{9}$$

where $\Psi = [\vec{\psi}_1, \vec{\psi}_2, \vec{\psi}_3]$ and $\Lambda = [\lambda_1, \lambda_2, \lambda_3](\lambda_1 \geq \lambda_2 \geq \lambda_3)$ represent the eigenvectors and eigenvalues, respectively. Two eigenvectors, $\vec{\psi}_2$ and $\vec{\psi}_3$, that correspond to smallest eigenvalues, λ_2 and λ_3, represent two directions with smallest spread of $\vec{X}_i$'s (i. e. RGB values of skin pixels). A 2D lookup table (i. e. color histogram) is built by projecting all $\vec{X}_i$'s onto the 2D plane defined by the two axes, $\vec{\psi}_2$ and $\vec{\psi}_3$, as in (10). This lookup table is loaded for the segmentation of skin colors. $\mathrm{W}_{\mathrm{pca}}$ is a linear projection matrix of which two column vectors are $\vec{\psi}_2$ and $\vec{\psi}_3$.

$$\vec{Y}_i = \mathrm{W}_{\mathrm{pca}}^T \vec{Y} \vec{X}_i \tag{10}$$

III. A Simple Lookup Table Method for Performance Comparison

We have implemented a simple lookup table method for skin color segmentation to compare the segmentation performance of the proposed chrominance plane with those of the HS and IQ planes. Its block diagram is shown in Fig. 4. The current user is asked to place his or her hand for a very short period of time in a prespecified area of the camera's view to obtain training images as shown in Fig. 2. We preprocess the input image using the retinex algorithm. We collect skin colors of the current user. We repeat this until the desired number of training images is processed. We apply PCA techniques to the RGB values of skin colors collected and get a linear projection matrix of which the columns are vectors representing two axes computed by the PCA analysis. We build a color histogram based on the plane formed by these two axes. They correspond to directions of smallest spread of the RGB values of skin pixels.

During segmentation, the input image is preprocessed by the retinex algorithm. RGB values of each pixel in the input image are projected onto the chrominance plane using the linear projection matrix computed from online training. The pixel is simply classified as a skin pixel if it is one of the entries in the lookup table. In the case of the HS and IQ planes, the dotted parts in Fig. 4 are replaced by an operation that converts RGB coordinates into the HSI or YIQ color coordinates, respectively. For fair comparisons, we have applied the same online training and retinex algorithm to the HS and IQ based cases.

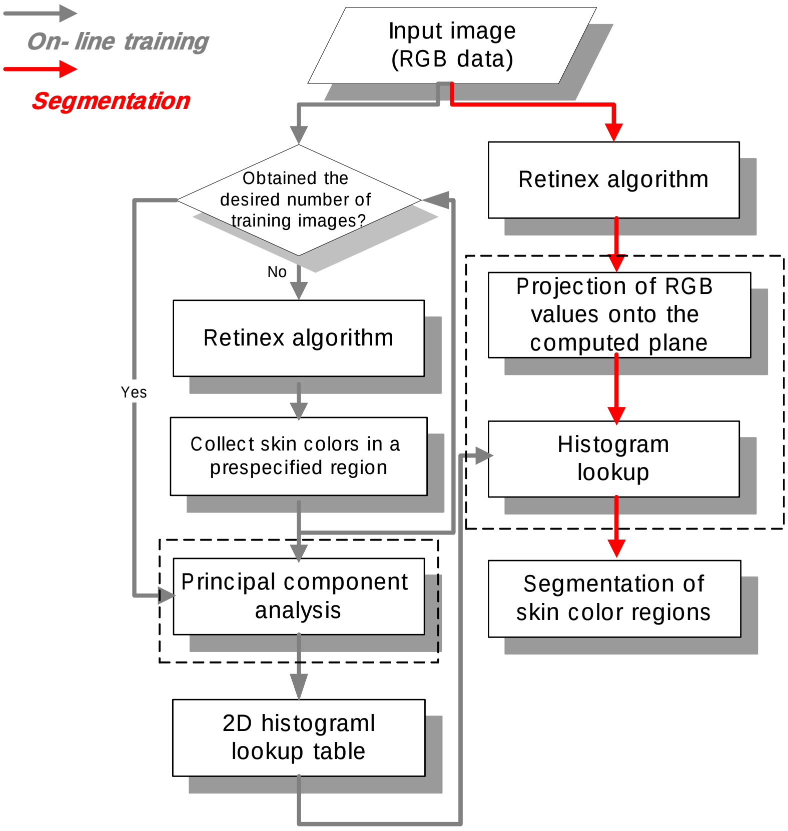


Fig. 4 a simple color histogram lookup algorithm for skin color segmentation to evaluate the performance of the proposed chrominance plane

IV. Experimental Results

It is meaningful to check out the retinex effect on the distribution of skin color in the histogram. Fig. 5 shows an example of histograms in the respective chrominance planes of a person before and after the retinex algorithm is applied. We have observed that, in the proposed plane, histograms form a tight cluster and are not variant irrespective of the application of the retinex algorithm. On the other hand, the histo grams using the HS or IQ planes are changed a lot by the application of the retinex algorithm. This experimentally proves that the proposed plane provides good performance in color constancy. Fig. 6 shows segmentation results of hand regions. The proposed plane gave better segmentation results than the HS or IQ planes. We could improve the segmentation result by postprocessing such as the application of morphology operations. However, we intentionally did not include postprocessing for the purpose of focusing on pure evaluation of the chrominance plane

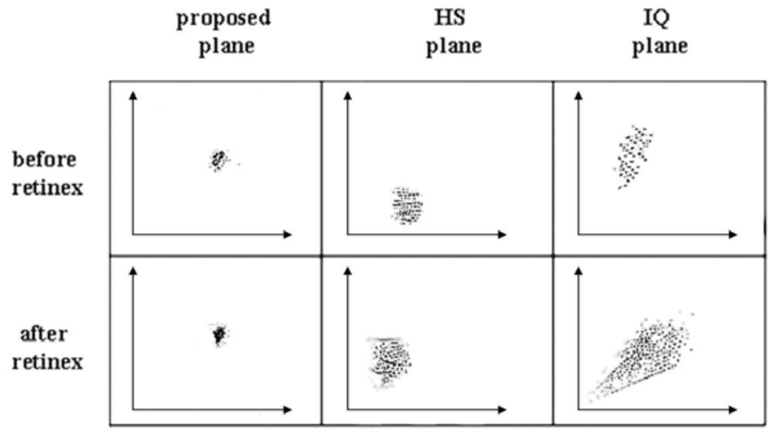


Fig. 5 examples of color histograms based on the proposed plane, HS plane and IQ plane before and after the retinex algorithm is applied. Note that in the cases of HS and IQ planes, the distribution of skin colors has changed a lot after the retinex algorithm is applied.

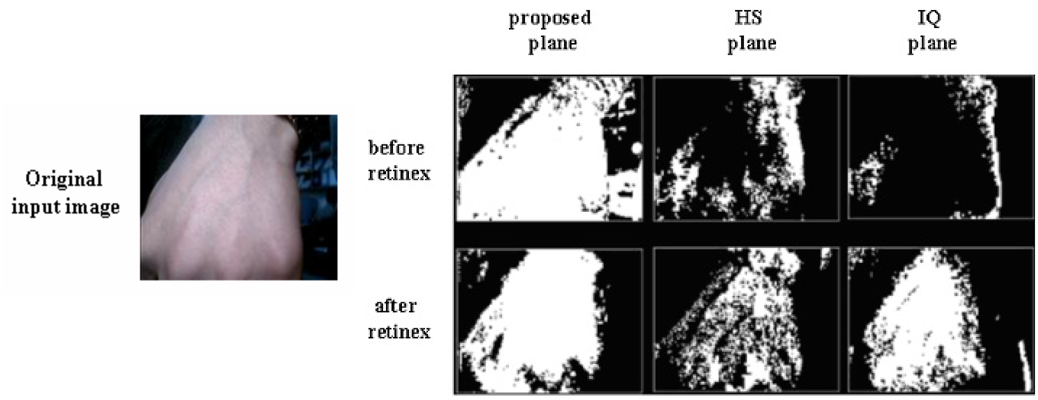


Fig. 6 segmentation results of hand regions: The retinex algorithm had more positive effects on the case of HS and IQ planes and significantly improved the segmentation results.

itself. As can be seen in the result, the retinex algorithm had more positive effects on the cases of HS and IQ planes and significantly improved the segmentation performance. The retinex algorithm has greatly changed the distribution of skin colors in the histogram for the HS and IQ planes.

We have successfully applied the proposed chrominance plane for skin color segmentation to two application systems that we recently developed in our lab. Fig. 7 (a) shows a system that efficiently tracks the fingertip of the index finger for the propose of application to a human mouse. In order to reliably detect human hand regions, we have employed the method just presented to train skin color distribution. Fig. 7 (b) shows a computer vision based interactive boxing game. There are four action menus; move left or right, and throw left or right punch. We have implemented the game as playable and enjoyable using simple vision algorithms. The same color segmentation method has been used in this system to detect skin regions and glove regions. In both systems, our chrominance plane provided better segmentation performance than the HS and IQ planes.

(a) (b)

Fig. 7 two application systems where the proposed chrominance plane for color segmentation is employed: (a) fingertip tracking system (b) interactive boxing game

V. Conclusions

Based on the fact that skin colors in the RGB color space are approximately distributed in a linear fashion, we have proposed a novel chrominance plane in the RGB color space for skin color segmentation. The chrominance plane is simply computed by online PCA analysis of skin colors. The idea is simple but works well. The proposed plane has better property in color constancy than the HS and IQ planes. In addition, the RGB color values of the input image do not need to be converted into HSI or YIQ color coordinates that have popularly been used for color segmentation. The experimental results show that the performance of skin color segmentation using the proposed plane is much more robust to illumination and pose changes compared to those using HS or IQ planes.

Acknowledgment

This work was supported in part by the Korea Science and Engineering Foundation (KOSEF) through the Biometrics Engineering Research Center (BERC) at Yonsei University and the intelligent robotics frontier R&D program funded by the Ministry of commerce, industry and energy of Korea.

References

[1] R. Kjeldsen and J. Kender, "Finding Skin in Color Images," International Conference on Automatic Face and Gesture Recognition. (1995)

[2] F. Quek, T. Mysliwiec, and M. Zhao, FingerMouse, "A Freehand Pointing Interface," Proceedings of IEEE International Conference on Automatic Face and Gesture Recognition. (1995) 372-376

[3] Leonid Sigal, Stan Sclaroff, and Vassilis Athitsos, "Estimation and Prediction of Evolving Color Distributions for Skin Segmentation Under Varying Illumination," Proceedings of IEEE Conference on omputer Society Conference on Computer Vision and Pattern Recognition. (2000) 152-1594.

[4] Rogerio Schmidt Feris, Teofilo Emidio de Campos, and Roberto Marcondes Cesar Junior, "Detection and Tracking of Facial Features in Video Sequences," Springer-Verlag press MICAI-2000. (1793) 197-206

[5] M. J. Swain and D. H. Ballard, "Color Indexing," International Journal of Computer Vision. (1991) 11-32

[6] Jung Soh, Ho-Sub Yoon, Min Wang and Byung-Woo Min "Locating Hands in Complex Images Using Color Analysis," IEEE International Conference on Computational Cybernetics and Simulation. (1997) 2142-2146

[7] M. Mottleb and A. Elgammal, "Face Detection in Complex Environment from Color Images," International Conference on Pattern Recognition, vol. 3. (1999) 622-626

[8] Daniel J. Jobson, Zia-ur-Rahman, "Propertied and Performance of a Center/Surround Retinex," IEEE Transaction on image processing, vol. 6. (1997) 451-462

[9] Zia-ur Rahman, Daniel J. Jobson and Glenn A. Woodell, "Multi-Scale Retinex for Color Image Enhancement," Proceedings of the IEEE International Conference on Image processing, vol. 3. (1996) 16-19

[10] E. Land, "An alternative technique for the computation of the designator in the retinex theory of color vision," in Proc. Nat. Acad. Sci, vol. 83. (1986) 3078-3080

Cheol-Hwon Kim received the B.S and M.S. degrees in Electrical and Computer Engineering from Sungkyunkwan University, Korea, in 2002 and 2004, respectively.
He is currently working as a system engineer at NextEye Co., Ltd. His primary research interests include object shape recovery using structured light.

June-Ho Yi received the B.S. degree from the Seoul National University, Seoul, Korea, in 1985, the M. S. degree from the Pennsylvania State University, University Park, PA, in 1987, and the Ph.D. degree from Purdue University in 1994, all in Electrical and Computer Engineering.
In 1989, he was a research scientist at the Samsung Advanced Institute of Technology. From 1994 to 1995, he was a research scientist at the University of California, Riverside. From 1995 to 1996, he was a senior research scientist at the Korea Institute of Science and Technology, Seoul, Korea. In 1997, he joined Sungkyunkwan University, Korea, and he is currently an associate professor of School of Information and Communication Engineering. His research interests are broadly in the areas of computer vision and vision-based computer interaction.