Colour Image Segmentation Using Relative Values of RGB in Various Illumination Circumstances

Chiunhsiun Lin, Ching-Hung Su, Hsuan Shu Huang, and Kuo-Chin Fan

Abstract— We propose a novel colour segmentation algorithm can work in various illumination circumstances. The proposed colour segmentation algorithm operates directly on RGB colour space without the need of colour space transformation and it is very robust to various illumination conditions. Our approach can be employed in various domains (e.g., human skin colour segmentation, the maturity of tomatoes). Furthermore, our approach has the benefits of being insensitive to rotation, scaling, and translation. In addition, the system can be applied to different applications, for example, colour segmentation for fruits (vegetables) quality control by merely changing the values of the parameters (α, $\beta 1$, $\beta 2$, $\gamma 1$, $\gamma 2$). Experimental results demonstrate the practicability of our proposed approach in colour segmentation.

Keywords— Colour segmentation, Image processing, Skin detection, Quality control, RGB colour space.

I. Introduction

SEGMENTATION is one of the basic techniques in computer vision [1, 2]. Colour is often thought as a property of an individual object. The colour of object comes from the visible light that reflects at the object surface. From the engineering viewpoint, visible light consists of a small part of electromagnetic radiation from 380 nm to 780 nm in the wavelength domain. Since computer systems were not robust enough to operate large and true-colour images before, researches focused on segmenting grey scale images instead of true-colour images. Currently, the computer systems are already robust enough to handle large and true-colour images. What is more, colour segmentation possesses the advantages of being insensitive to rotation, scaling, and translation. Therefore, colour segmentation becomes an important role in the area of quality control, image processing, pattern recognition, and computer vision. The visual appearance of food and other biological products is the foremost feature in the decision of quality, so visual inspection is the most important part of quality control in these areas. Using "the eyes of human being" has historically carried out these examinations. However, such inspections are time consuming and high cost.

Abundant research has been conducted on colour segmentation, and some successful approaches have been developed and reported in the literature. In the food manufacturing, according to the FSTA-data base, colour segmentation has been used in [3] grading of mushrooms, [4] presented an apple surface feature detection, Scanlon proposed an approach to quantify colour of potato chips [5], and Choi utilized colour image analysis to examine the maturity evaluation of tomatoes [6]. In the area of pattern recognition and computer vision, colour segmentation has been utilized in [7] located the poses of human faces and facial features from colour images. They presented a system that used an ellipse in Hue-Saturation-Value (HSV) colour space to express the shape of a face. Furthermore, they need the colour space transformation. Wu proposed a skin colour distribution function on an unchanged colour space to detect the face-like region. The skin colour regions in colour images were modelled as several 2-D patterns and verified with the built face model by a fuzzy pattern matching approach [8]. Yoo proposed a fast algorithm that is based on chromatic histogram and histogram back projection operation for tracking human face regions in colour motion images [9]. Jin used a luminance-conditional distribution model of skin-colour information is used to detect skin pixels in colour images. Next, morphological operations were used to extract skin-region rectangles. Lastly, they utilized template matching based on a linear transformation to detect face in each skin-region rectangle [10]. Meurie described a scheme to color image segmentation which is based on supervised pixel classification methods [11]. Puangdownreong proposed an approach to system identification via image processing techniques. Their approach permits non-intrusive and remote identification. One or more cameras can be an alternative to conventional sensors. Dynamical information of the system can be extracted from the recorded images [12]. Gribkov studied some properties of four digital image segmentation methods with the aid of their PICASSO (PICture Algorithms Study Software, program system [13]. Fahiem discussed an image based digital library specially meant for mechanical engineering objects. Their library is versatile since it stores images of engineering objects as (scalable vector graphics) SVG representations and supports textual as well as interactive search queries. Their library can be populated dynamically by the user [14]. Lin adopted colour in YCbCr colour space and triangle-based segmentation to search potential face regions, and involved face verification using a multilayer feedforward neural network [15]. Sun suggested a new approach for detecting skin in a single image. Their approach uses a local skin model to shift a globally trained skin model to adapt the final skin model to the current image. [16] Jedynak considered a sequence of three models for skin detection built from a large collection of labeled images. Each model is a maximum entropy model with respect to constraints concerning marginal distributions. The first model, called the baseline model is well known from practitioners. Pixels are considered independent. Performance, measured by the ROC curve on the Compaq Database is impressive for such a simple model. However, single image examination reveals very irregular results. The second model is a Hidden Markov model, which includes constraints that force smoothness of the solution. The ROC curve obtained shows better performance than the baseline model. Finally, color gradient is included, they obtain a simple analytical expression for the coefficients of the associated maximum entropy model. [17]. Jones described the construction of color models for skin and non-skin classes from a dataset of nearly 1 billion labelled pixels. These classes exhibit a surprising degree of separability which we exploit by building a skin pixel detector achieving a detection rate of 80% with 8.5% false positives. They compare the performance of histogram and mixture models in skin detection and find histogram models to be superior in accuracy and computational cost.[18]. El Fkihi presented a new algorithm based on the Optimal-Spanning-Tree (OST) distributions. An OST is widely used in many disciplines as a way to approximate the true class probability; however, it is not necessarily unique. They suggested the mixture of the K-Optimal-Spanning-Trees to deal with the problem of classification and/or probability approximation [19].

In this paper, we propose a novel colour segmentation algorithm based on the derived inherent properties of RGB colour space. The proposed algorithm is robust to various illumination environments and can operate directly on RGB colour space without the need of colour space transformation.

II. Colour Segmentation of Human Skin Colour

RGB colour space is the most common colour representation that has been adopted in large amount input/output devices for colour information.

An RGB color space can be easily understood by thinking of it as "all possible colors" that can be made from three colour ants for red, green and blue. Imagine, for example, shining three lights together onto a white wall: one red light, one green light, and one blue light, each with dimmer switches. If only the red light is on, the wall will look red. If only the green light is on, the wall will look green. If the red and green lights are on together, the wall will look yellow. Dim the red light some and the wall will become more of a yellow-green. Dim the green light instead, and the wall will become more orange. Bringing up the blue light a bit will cause the orange to become less saturated and more whitish. In all, each setting of the three dimmer switches will produce a different result, either in color or in brightness or both. The set of all possible results is the gamut defined by those particular color light bulbs. Swap out the red light bulb for one of a different brand that is slightly more orange, and there will be slightly different gamut, since the set of all colors that can be produced with the three lights will be changed. The RGB cube can be showed as Figure 1.

There are two versions of RGB colour representation, which are NTSC-(RGB) and CIE-(RGB). Here, we use the NTSC-(RGB) version. NTSC-(RGB) colour space is a 3-dimensional vector space, and each pixel, p (i), is defined by an ordered triple of red, green, and blue coordinates, (r (i), g (i), b (i)), which represent the intensities of red, green, and blue light respectively.

The proposed scheme is realized by careful observing the inherent properties of RGB colour space as shown in Figure 2, where Figure 2 (a) depicts the r, g, b values of some colours of human skin. For example, as displayed in Figure 2 (a), line (1) has (r, g, b) = (203,161,136) corresponding to ″skin-like-colour 1″, line (3) has (r, g, b) = (212,162,119) corresponding to ″skin-like-colour 3″, line (5) has (r, g, b) = (191,137,111) corresponding to ″skin-like-colour 5″ and so on. We find that the value of (r – g) is between 28~56. We also find that the value of (r – b) is about 49~98 since the imaging effect and imperfect skin colours. From the observation, we realize that the absolute values of r, g, and b are totally different with the altered illumination conditions. Conversely, the relative values between r, g, and b are almost unchanged with the various illumination circumstances.

To verify this, we conduct experiments on the original 32-bit-colour map. Figure 2 (b) is the original 32-bit-colour map. Figure 2 (c) displays the result of colour segmentation. From Figures 2, we discover that the relative value between r, g, and b is roughly similar with the various illumination circumstances. Next, we conduct numerous experiments (testing by real images) and discover that the relative values between r, g, and b are approximately the same. Therefore, we obtain 3 rules for the task of human skin colour segmentation:

1. r (i) > α: means that the primary colour component (red) should be larger than α.

2. β1 < (r (i) – g (i)) < β2: means that the primary colour component (red – green) should be between β1 and β2.

3. γ1 < (r (i) – b (i)) < γ2: means that the primary colour component (red – blue) should be between γ1 and γ2.

The value of "α" = 80, "β1" = 0, "β2" = 56, "γ1" = 0, and "γ2" = 98 are experimentally found to be satisfactory in the human skin colour segmentation. The first rule means that the value of r (i) — the intensity of red light should be larger than α. The second rule means that the value of (r (i) – g (i)) — (the intensity of red light) - (the intensity of green light) should be between β1 and β2. The third rule means that the value of (r (i) – b (i)) — (the intensity of red light) - (the intensity of blue light) should be between γ1 and γ2. In other words, if the pixels of the input image satisfy the above 3 rules, then the pixels are regarded as skin colour. You can give (α, β1, β2, γ1, γ2) different values for distinct applications, and the output will be altered.

III. Experimental Results

In this section, two sets of experimental results are demonstrated to verify the effectiveness and efficiency of our system.

The first set as demonstrated in Figures 3 and 4. Figure 3(a) illustrated the original input RGB colour image, Figure 3 (b) exemplified the result of human skin colour segmentation — only the skin colour will be remained. Figures 4 displayed one example of our experiment about illumination condition. Figure 4 (a) is the original input RGB colour image, Figure 4 (b) exhibited the result of human skin colour segmentation of Figure 4 (a); Figure 4 (c) is the darker input RGB colour image, Figure 3(d) showed the result of human skin colour segmentation of Figure 4 (c); Figure 4 (e) is the lighter input RGB colour image, Figure 4 (f) demonstrated the result of human skin colour segmentation of Figure 4 (e). Obviously, human skin colour segmentation cannot satisfactorily work in all case. Therefore, we assume the input images should not be too dark or too light. For example, the input images with altered lighting conditions as showed in Figure 4 are expected.

Examples illustrating that our skin colour segmentation scheme is robust to different people/race and illumination conditions are shown as Figure 5.

We compare our new approach with the systems of [17, 18, and 19]. Experiments with these models are presented in Figure 6. The input of each system is a colour image and the output is a gray image scale. The first system is our new approach. The second system is the baseline one in which pixels are considered independent [18]. It does not take into account the fact that skin zones are not purely random but are made of large regions with regular shapes [19]. The other systems correspond to the mixture of K-Spanning-Trees processes (K = 2, 3, 4). We can assert ours is better than the others.

With the idea (we can give (α, β1, β2, γ1, γ2) different values for distinct applications, and the output will be altered.) in the second section, we simply change the values of the parameters (α, β1, β2, γ1, γ2), and we can use almost the same rules to examine the maturity evaluation of tomatoes. The values are: α = 20、β1 = 0、β2 = 110 、γ1 = 20、γ2 = 160. The second set as shown in Figures 7 illustrated one example of examining the maturity evaluation of tomatoes. Figure 7 (a) is the original input RGB colour image, Figure 7 (b) demonstrated the result of colour segmentation — only the maturity tomatoes colour will be remained. Figures 8 illustrated one example of our experiment about illumination condition. Figure 8 (a) is the lighter input RGB colour image, Figure 8 (b) exemplified the result of colour segmentation of Figure 8 (a) — only the maturity tomatoes colour will be remained, Figure 8 (c) is the darker input RGB colour image, Figure 8 (d) displayed the result of colour segmentation of Figure 8 (c). Figure 8 (e) is the original input RGB colour image; Figure 8 (f) exhibited the result of colour segmentation of Figure 8 (e).

After the colour segmentation of tomatoes, we can only calculate the rate of R = (the number of the maturity tomatoes colour) / (the number of NOT the maturity tomatoes colour). Then it will be straightforward to estimate the maturity tomatoes by R — the higher R means the higher maturity.

IV. Conclusion

In this paper, a novel colour segmentation algorithm that can examine the maturity evaluation of tomatoes and extract the human skin colour is proposed. Our system is based on the derived inherent properties of RGB colour space The proposed colour segmentation algorithm is very effective in extracting human skin colour and examining the maturity evaluation of tomatoes. This system is very robust to numerous illumination conditions by operating directly on RGB colour space without the need of colour space transformation. Moreover, the system can be applied to different applications without difficulty; for example, it can be used for food, drug, and PCB quality control or inspection by merely changing the values of the parameters (α, β1, β2, γ1, γ2). In the future, we will use the colour segmentation algorithm in other applications, for example, content based image retrieval (CBIR).

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Chiunhsiun Lin was born on 5 December 1961 in Chia-yi, Taiwan, Republic of China. He received his Ph.D. degrees in Institute of Computer Science and Information Engineering, National Central University, Chung-Li, Taiwan, in 2001. He was an assistant researcher in Committee for Planning and Organizing the National Taipei University from 1995 to January 2000, and he was an assistant researcher in the Information Center of National Taipei University from February 2000 to July 2002. From August 2002, he was an associate researcher in the Information Center of National Taipei University. From September 2004, he is an associate researcher in the Office of Research and Development Affairs of National Taipei University. His current researches interests include pattern recognition, image processing, and computer vision, face detection, face recognition, CBIR, CVIR. He is a senior member of the IACSIT (International Association of Computer Science and Information Technology). He received the Outstanding Researcher Awards granted by the National Taipei University, Taiwan, in 2004. He is reviewers of "IEEE Transactions on Image Processing", "Pattern Recognition Letters", "Journal of Visual Communication and Image Representation", "IET Image Processing", "Machine Vision and Applications", "Applied Intelligence" and "Information Sciences".

Ching-Hung Su received the B.S. degree in computer science from Tamkang University, Taipei, Taiwan, in 1979 and the M.S. degree in computer science from City University of New York, New York City, in 1985. During 1986–1990, he served as Assistant Researcher for Telecommunication Laboratories, Taoyuan, Taiwan. In 1990, he joined the faculty of the Department of Electronic Engineering, Lunghwa University of Science and Technology, Taoyuan, where he is currently a lecturer. His research interests include digital image processing and CBIR.

Kuo-Chin Fan (M'88) was born in Hsinchu,, Taiwan, R.O.C. in 1959. He received the B.S. degree in electrical engineering from National Tsing Hua University, Hsinchu, Taiwan, R.O.C., in 1981 and the M.S. and Ph.D. degrees from the University of Florida, Gainesville, in 1985 and 1989, respectively In 1983, he joined the Electronic Research and Service Organization (ERSO), Taiwan, as a Computer Engineer. From 1984 to 1989, he was a Research Assistant with the Center for Information Research, the University of Florida. In 1989, he joined the Institute of Computer Science and Information Engineering, National Central University, Chung-Li, Taiwan, where he became a Professor in 1994. From 1994 to 1997, he was the Chairman of the department. He was the Director of the Software Research Center from 1998 to 2000 and Director of the Computer Center from 1999 to 2003, National Central University. Currently, he is the Director of the Communication Research Center. He was the President of the Image Processing and Pattern Recognition Society-Taiwan from 2002 to 2004 and President of the governing board of the International Association of Pattern Recognition (IAPR) starting in 2002. His current research interests include biometrics identification, video surveillance, and intelligent transportation system Dr. Fan received three consecutive Outstanding Researcher Awards granted by the National Science Council, Taiwan, during 1998-2000.

Hsuan Shu Huang was born in Changhua, Taiwan, R.O.C. in 1976. He received the B.S. degree in Automatic Control from Feng Chia University, Taichung, Taiwan, R.O.C., in 1999 and the M.S. degree in electrical engineering from the National Central University in 2003. Currently, he works at National Taipei University Information center as a computer technician from 2004. His current research interests include biometrics identification, video retrieval, CBIR, CBVR, and video surveillance. He is also a member of Artificial Intelligence and Pattern Recognition Laboratory at NCU.

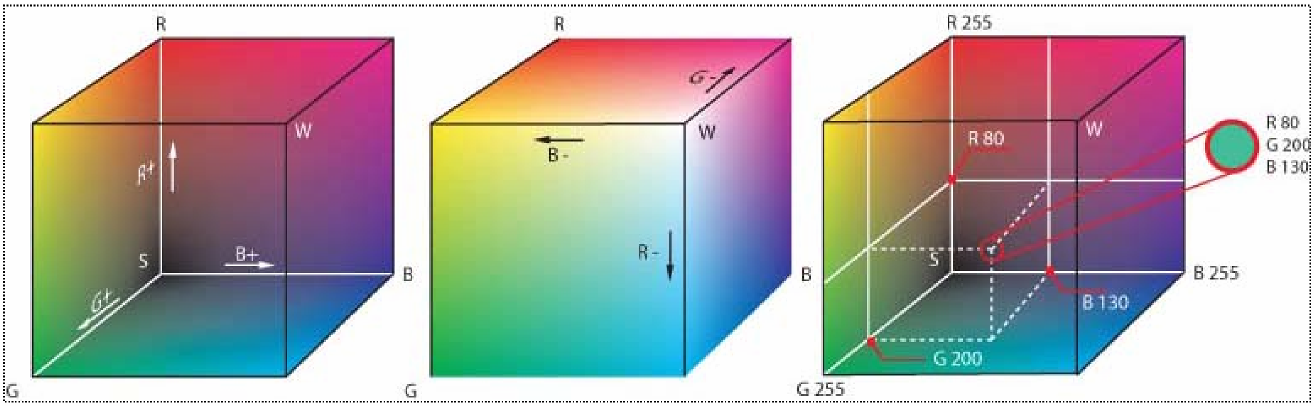

Fig. 1 RGB-Cube

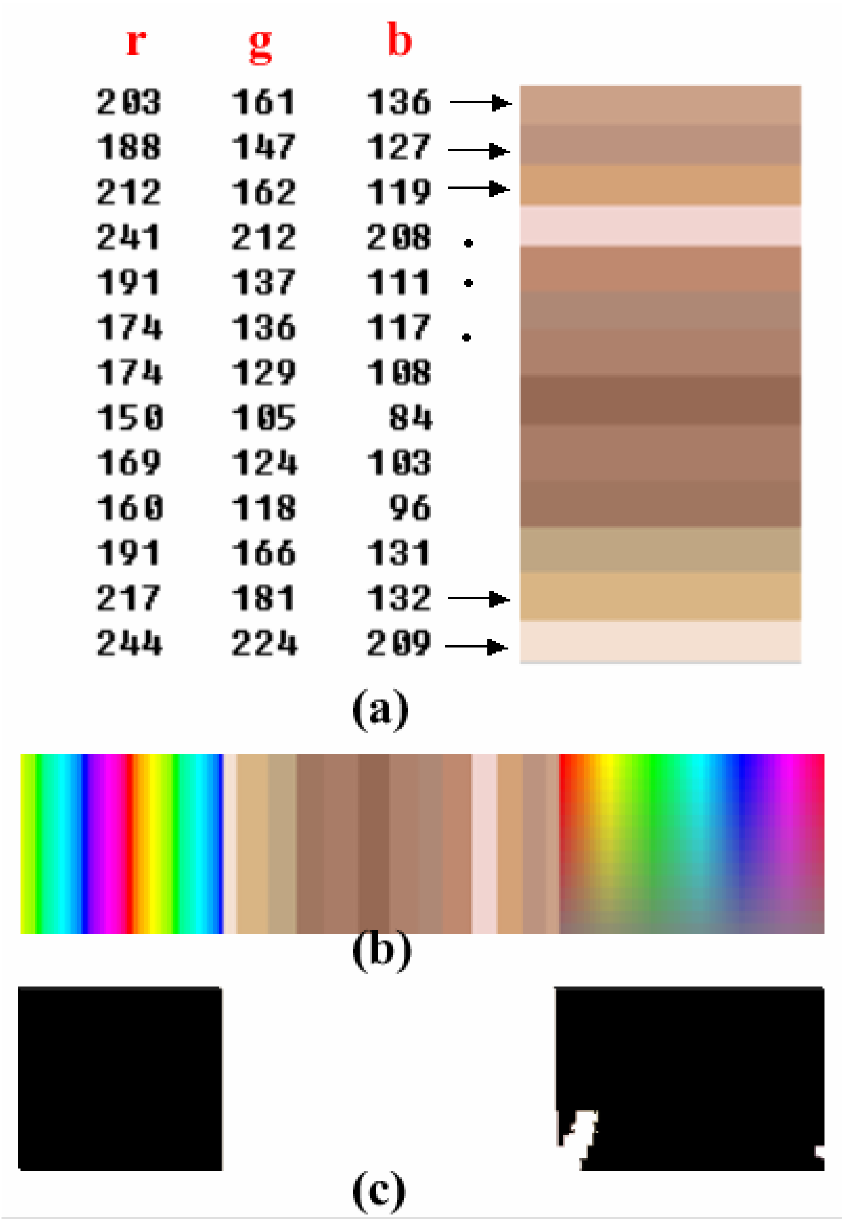

Fig. 2 human skin colour segmentation

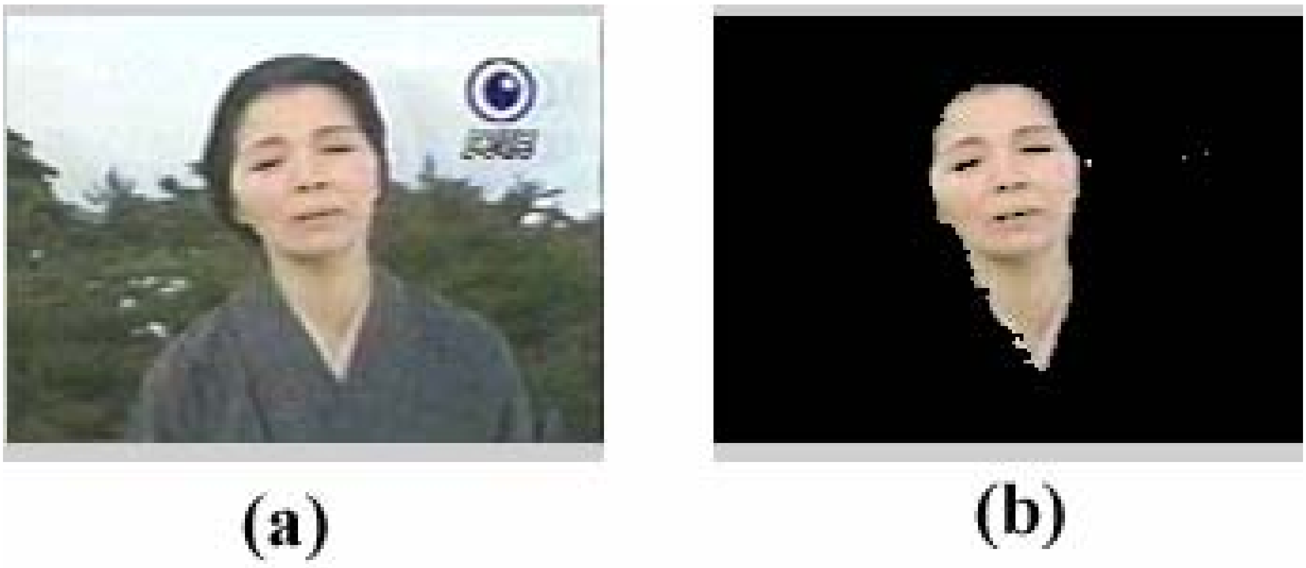

Fig. 3 one real example of Human skin colour segmentation

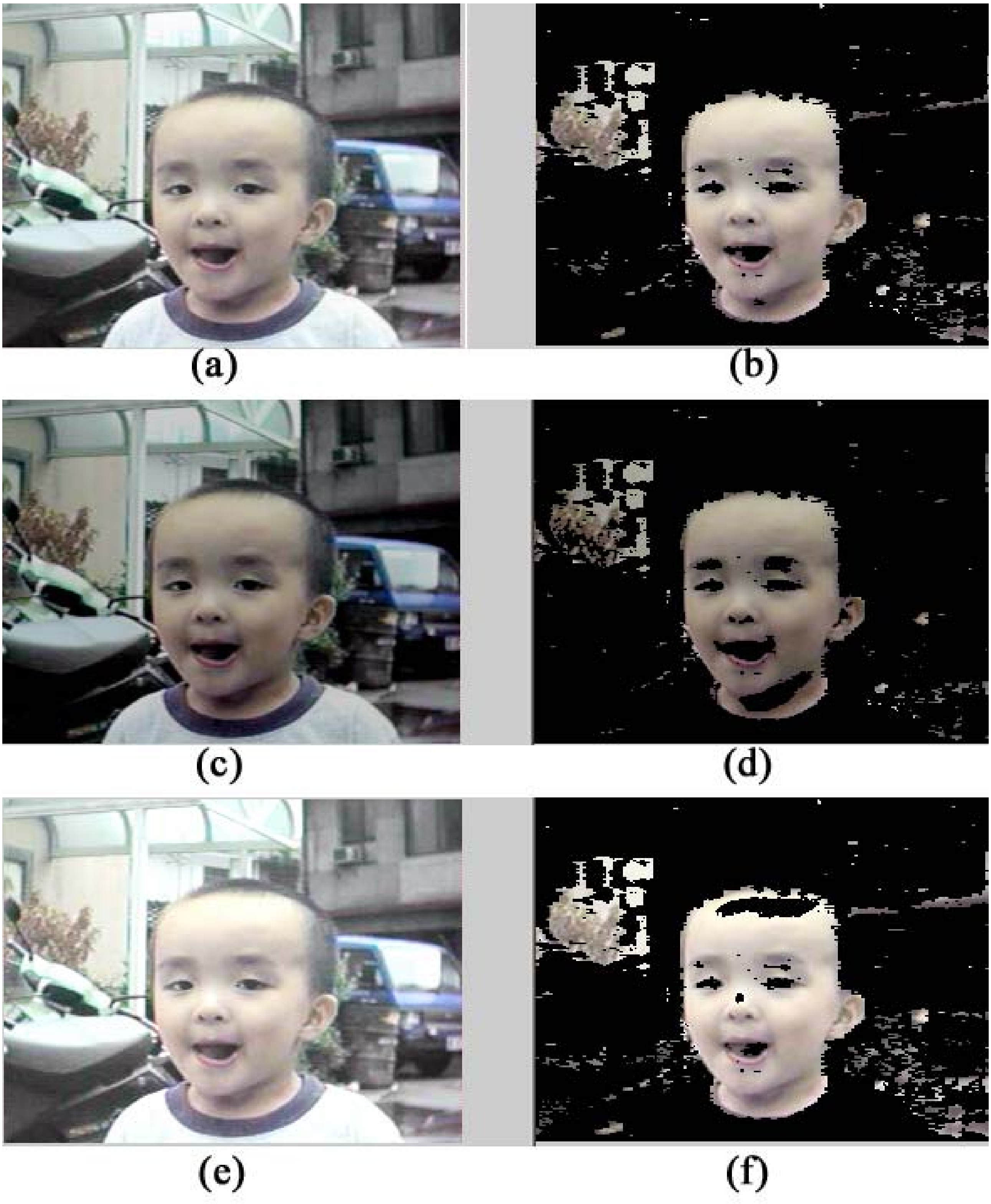

Fig. 4 examples illustrating the effect of light on human skin colour segmentation.

Fig. 5: examples illustrating that our skin colour segmentation scheme is robust to different people/race and illumination conditions.

Fig. 6 first column: original color images. Second column: the colour results of our approach. Third column: the gray results of our approach. Then (From left to right) the results of the baseline model, the results of the mixture of K-Optimal-Spanning-Trees model (K = 2, 3, 4).

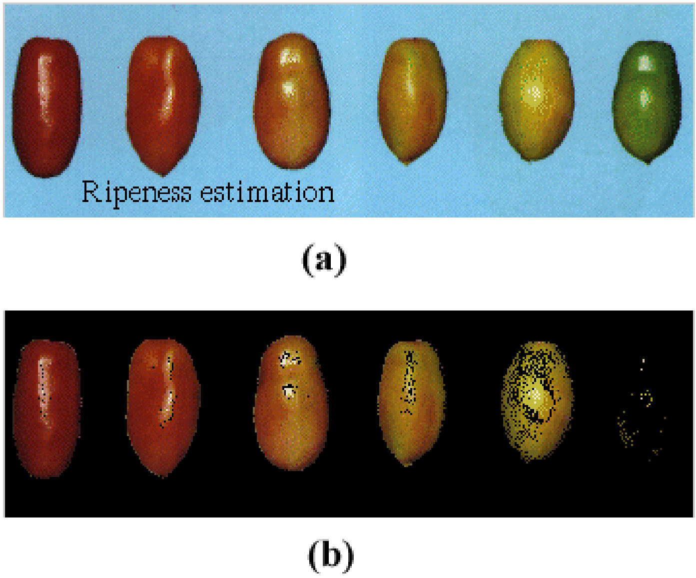

Fig. 7 the maturity evaluation of tomatoes by colour segmentation

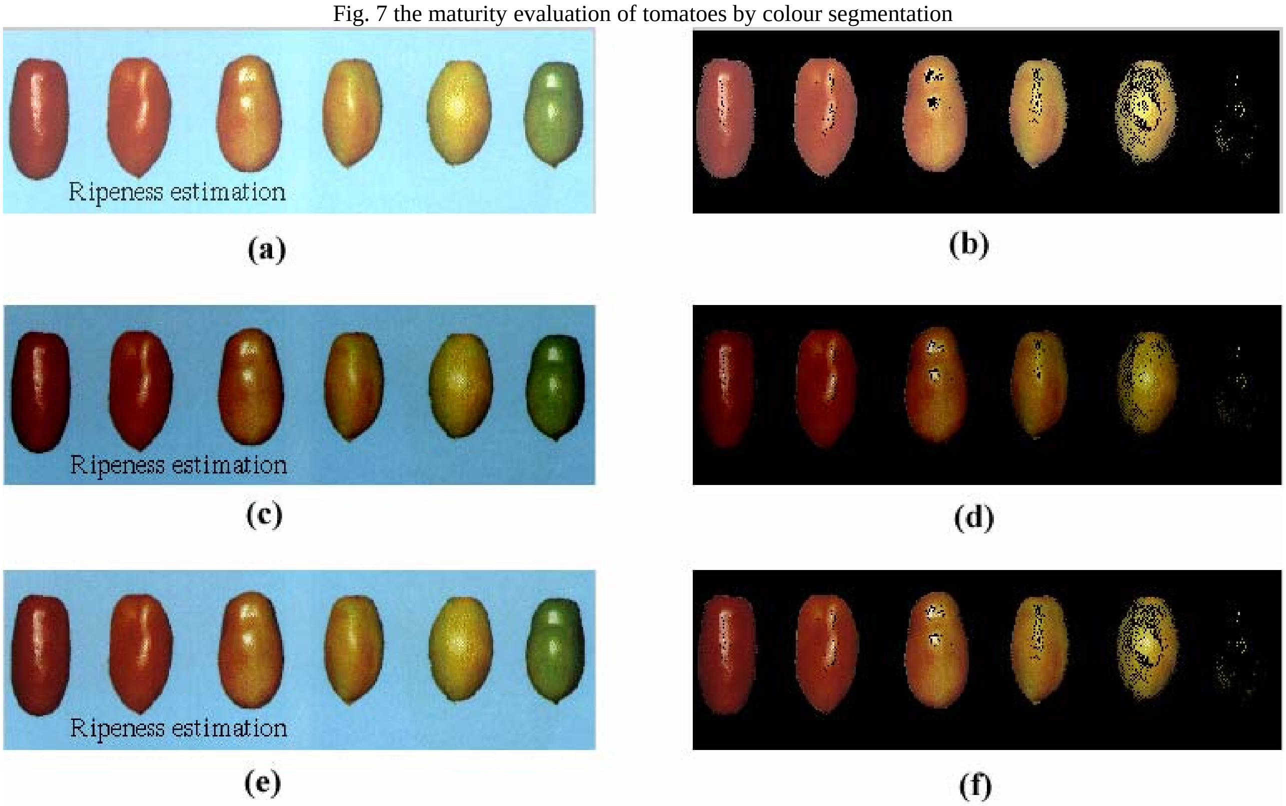

Fig. 8 evaluation the maturity of tomatoes with different illumination condition.