ENHANCED HUMAN SKIN COLOUR RETRIEVAL SYSTEM USING RGB RATIO MODEL

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Abstract: *Skin colour detection is frequently used for searching people, face detection, pornographic filtering and hand tracking. The presence of skin or non-skin in digital image can be determined by manipulating pixels' colour and/or pixels' texture. The main challenge of skin colour detection is to develop a classifier that is robust to the large variations in skin colour appearance. This process is difficult because the appearance of a skin colour in an image depends on the illumination conditions where the image was captured. Therefore, the main problem in skin colour detection is to represent the skin colour distribution model that is invariant or least sensitive to changes in illumination condition. Another problem comes from the fact that many objects in the real world may possess almost similar skin-tone colour such as wood, leather, skin-coloured clothing, hair and sand. Moreover, skin colour is different between races and can be different from a person to another, even with people of the same ethnicity. Finally, skin colour will appear a little different when different types of camera are used to capture the object or scene. The objective of this study is to develop a skin colour classifier based on pixel-based using RGB ratio method. This skin classifier was tested with SIdb dataset and two benchmark datasets; UChile and TDSD datasets to measure classifier performance. The performance of skin classifier was measured based on true positive (TF) and false positive (FP) indicator. The RGB ratio model is a newly proposed method that belongs under the category of an explicitly defined skin region model. This newly proposed model was compared with Kovac, Saleh and Swift models. The experimental results showed that the RGB ratio model outperformed all the other models in term of detection rate. The RGB ratio model is able to reduce FP detection that caused by reddish objects colour as well as be able to detect darkened skin and skin covered by shadow.*

Keywords: *Image processing, retrieval system, colour model, skin detection, image filtering, content-based information retrieval.*

INTRODUCTION

Skin is the largest organ of human body (Marks & Miller, 2006). It is a soft outer covering of human's muscles, bones, ligaments, and internal organs. Skin colour is produced by a combination of melanin, haemoglobin, carotene, and bilirubin. Haemoglobin gives blood a reddish colour or bluish colour while carotene and bilirubin give skin a yellowish appearance. The amount of melanin makes skin appear darker (Anderson & Parrish, 1982). Due to its vast application in many areas, skin colour detection research is becoming increasingly popular among the computer vision research community. Today, skin colour detection is often used as pre-processing in some applications such as face detection (Chen & Chiang, 1997a; Pham The et al., 2005; Berbar et al., 2006; Harasse et al., 2006; Heesung et al., 2006; Hosub et al., 2006; Jong-Il & Kyoung-Kwan, 2006), pornographic image detection (Fleck et al., 1996; Jiao et al., 2001; Cao et al., 2002; Schettinia et al., 2003; Liang et al., 2004; Zheng et al., 2004; Zhu et al., 2004; Ruiz-Del-Solar et al., 2005; Wang et al., 2005; Xu et al., 2005; Kelly et al., 2008), hand gesture analysis (Yang & Ahuja, 2001), people detection, content-based information retrieval, to name a few.

The skin colour fills only a small fraction from the whole colour model and thus, any frequent appearance in an image could be a clue to human presence. Another feature to identify skin colour region is its texture properties. A skin colour modelling typically transforms a given pixel into an appropriate colour model and then uses a skin colour classifier to label the pixel whether it is a skin or a non-skin pixel. A skin colour classifier defines a decision boundary of the skin colour pixels in the selected colour model based on database of skin-coloured pixels. Skin colour provides computationally effective, robust information against rotations, scaling, and partial occlusions (Kakumanu et al., 2007). Skin colour can also be used as complimentary information to other features such as shape, texture, and geometry.

Skin colour detection is a process to determine whether a desired pixel belongs to skin or non-skin pixels in a digital image or a video. In other words, for a still image, skin colour detection is a task where an image is provided as input to the process and its output is a set of positions of skin pixels or non-skin pixels. The process of skin detection involved the classification technique, which can be carried out at an individual pixel or a group of pixels. Thus, skin classification technique can be categorised into two categories, i.e. pixel-based and region-based. The pixel-based skin classification is carried out at pixel level where each pixel is classified separately based on its colour properties. On the other hand, region-based skin classification is carried out based on a group of pixels, where spatial arrangement of a group of pixel properties was taken into consideration.

There are two categories of features that can be extracted from image as input to detect the presence of skin or non-skin pixels, namely skin colour and skin texture. From image processing perspective, skin colour detection is a process of detecting the presence of human in an image. According to Kakumanu et al. (2007), most of the researches as reported in this area were focused on detecting human skin colour based on colour properties. This fact could be due to skin colour is invariant in term of size and orientation (Boissaid et al., 2005). Another reason for its popularity is its fast processing as compared to other methods (Vezhnevets et al., 2003).

A simple technique for skin detection modelling is to implement one or several thresholds (Kovac et al., 2003b; Saleh, 2004; Swift, 2006) to decide whether a pixel is skin or non-skin. A more advance modelling technique employing statistical based approaches such as neural network (Bourbakis et al., 2007), Bayesian (Chai et al., 2003), maximum entropy (Jedynak et al., 2002) and k-means clustering (Ravichandran & Ananthi, 2009) have also been used to detect skin colour pixel. Many different modelling techniques for discriminating between skin and non-skin regions are available in the literature. The skin distribution modelling techniques can be grouped into four types (Vezhnevets et al., 2003), i.e. explicitly defined skin region, parametric, non-parametric, and dynamic skin distribution modelling techniques.

An explicitly defined skin colour region modelling is perhaps the simplest method often employed by researchers. This method used to formulate skin detection classifier, which is defined by the boundaries of the skin region in certain colour coordinates in appropriately chosen colour model. This method is very popular among the researchers (Tsekeridou & Pitas, 1998; Chai & Ngan, 1999; Garcia & Tziritas, 1999; Brand & Mason, 2000; Gomez & Morales, 2002; Hsieh et al., 2002; Lee & Yoo, 2002; Kovac et al., 2003b; Kukhareu & Novosielski, 2004; Saleh, 2004) because it is easy to implement and do not require a training phase. However, the main problem of this method is, it is difficult to achieve high accuracy in skin detection.

Problem Statement

Detecting skin-coloured pixels, although it seems as a straight forward and easy task, it has been proven to be quite challenging for many reasons. This is because the appearance of a skin colour in an image depends on the illumination conditions where the image was captured. Therefore, a major challenge in skin colour detection is to represent the skin colour distribution model that is invariant or least sensitive to changes in illumination condition. In addition, the choice of colour model used for skin colour detection modelling could significantly affects the performance of any skin colour distribution methods. Another challenge comes from the fact that many objects in the real world may have almost similar skin-tone colour such as wood, leather, skin-coloured clothing, hair, sand, etc. Moreover, skin colour is different between human races and can be different from a person to another, even with people of the same ethnicity. Finally, skin colour will appear a little different when different types of camera are used to capture the object or scene.

The main problem of skin colour detection is to develop a skin colour detection algorithm or classifier that is robust to the large variations in colour appearance. Some objects may have almost similar skin-tone colour which easily confused with skin colour. A skin colour can be vary in appearance base on changes in background colour, illumination, and location of light sources, and other objects within the scene may cast shadows or reflect additional light.

Secondly, there are no specific methods or techniques that have been proposed to robust skin colour detection arise under varying lighting conditions, especially when the illumination colour changes. This condition may occur in both out-door and in-door environments with mixture of day light and artificial light.

Thirdly, many non-skin colour objects are overlapping with skin colour, and most of pixel-based method proposed in the literature cannot solve this problem. This problem is difficult to be solved because skin-like materials are those objects that appear to be skin-coloured under a certain illumination condition.

In order to enable skin colour detection to cope with the above-mentioned problems, the objective of this study is to enhance a skin colour detection system by using RGB ratio method.

To achieve the aforementioned objective, a new skin images dataset have been developed for training and testing. Besides that, a benchmark skin images from Testing Database for Skin Detection (TDSD) (Zhu et al., 2004) and Skin image dataset from Universidad de Chile (UChile) (Ruiz-Del-Solar & Verschae, 2006) datasets have been used for benchmarking the performance of skin colour classifier that derived from RGB ratio method.

LITERATURE REVIEW

Skin detection process can be defined as a process to determine whether such pixels are either skin pixels or non-skin pixels. This skin detection process has two phases as follows (Elgammal et al., 2009):

i. Training phase
ii. Detection phase

A training phase involves four basic steps:

i. Collecting a database of skin and non-skin patches from different images. Such a database typically contains skin-coloured patches from people of different skin and non-skin colour under different illumination conditions.
ii. Choosing a suitable colour model to represent skin colour.
iii. Testing the skin colour detection model performance, and
iv. If necessary fine-tuning the skin colour classifier parameter to get optimum skin colour detection rate.

The process of skin colour detection for a given image will involve a process of transforming the tested image into the same colour model that is used in the training phase, and then, using skin colour classifier derived at the training phase to classify each pixel of a given image to either skin or non-skin pixel. In the context of skin colour detection, the true and false positive measure or true and false negative measure can be used to measure performance of the skin colour detection rate. The true positive (TP) is defined as skin pixel that is correctly classified as skin; and false positive (FP) is defined as non-skin pixel classified as skin. Meanwhile, false negative (FN) is defined as skin pixel classified as non-skin; and true negative (TN) is defined as non-skin pixel classified as non-skin pixel. Table 1 summarised the TP, FP, TN, and FN.

Table 1: True or false positive and true or false negative conditions for skin detection

		Given pixel	
Detected as		Skin	Non-skin
	Skin	True positive (TP)	False positive (FP)
	Non-skin	False negative (FN)	True negative (TN)

A good skin colour classifier should have low FP and FN rates. Similar to some other classification problems, there is a trade off between the increasing of FP and increasing of TP rate (Gomez, 2002; Phung et al., 2003). This is due to some overlapping colour between skin and non-skin colour. Thus, the colour model chosen for developing skin colour distribution model is important because it plays an important role in the performance of skin colour modelling technique (Fu et al., 2004). Another reason to choose suitable colour model for skin colour distribution modelling is that the colour model transformation is assumed to decrease the overlap between skin and non-skin pixels thereby aiding to skin colour detection as well as providing robust parameters against varying illumination conditions (Kakumanu et al., 2007).

In any given colour model, skin colour occupies a part of such a space, which might be a compact or large region in the space. Such region is usually called the skin colour cluster (Elgammal et al., 2009). Fleck and Forsyth (1996) highlighted that the human skin colour has a specific range of hues and is not deeply saturated, since the appearance of skin is formed by a combination of blood (red) and pigment melanin (brown, yellow). Therefore, the human skin colour does not fall randomly in a given colour model, but cluster at a small area in the colour model.

There are some surveys on skin colour distribution modelling (Zarit et al., 1999; Brand & Mason, 2000; Johansson, 2000; Terrillon et al., 2000; Duffield & Spencer, 2002; Vezhnevets et al., 2003; Vezhnevets & Andreeva, 2005; Kakumanu et al., 2007) in the literature. A comprehensive survey was carried out by Kakumanu et al. (2007). They provided a critical review of different skin colour modelling and skin detection methods. The performance of some skin detection methods with its usage of colour models (Vezhnevets et al., 2003; Kakumanu et al., 2007) were summarised in Table 2.2.

An overall performance evaluation of the reported methods is not possible due to different datasets used and different performance indicators were reported in these studies. Table 2.2 shows that some methods used the conclusion matrix approach (true or false positive indicator), whereas some authors who reported their findings using the Receiver Operating Characteristics (ROC) as a performance indicator, are stated as not applicable in Table 2.

Table 2: Performance of different skin detection method with the colour model used

Author	Colour model	Skin detection method	Performance	
			TP	FP
Jones & Rehg (1999)	RGB	Bayes	90%	14.2%
		GMM	90%	15.5%
Yang & Ahuja (1999)	LUV	GMM	N/A	N/A
Brand & Mason (2000)	RGB	Bayes	93.4%	19.8%
	YIQ	I-axis thresholding	94.7%	30.2%
	RGB	Thresholding ratio	94.7%	32.3%
Greenspan et al. (2001)	RGB	GMM	N/A	N/A
Brown et al. (2001)	TSL	SOM	78%	32%
Anagnostopoulos et al. (2002)	RGB	Fuzzy rules & PNN	82.4%	N/A

Thu & Meguro (2002)	HSV	GMM + Multi-thresholding	N/A	N/A
Marcel & Benigo (2002)	RGB	Histogram + MLP	N/A	N/A
Caetano et al. (2002)	RGB	SGM	76%	30%
	RGB	GMM	87%	30%
Jedynak et al. (2002)	RGB	Maximum entropy	82.9%	10%
Lee & Yoo (2002)	CIE-XYZ	Elliptical boundary	90%	20.9%
	RGB	Elliptical boundary	90%	21.3%
	YCbCr	SGM	90%	33.3%
	YIQ	SGM	90%	33.3%
	YIQ	GMM	90%	30%
Seow et al. (2003)	RGB	NN	N/A	N/A
Jayaram et al. (2004)	SCT	Bayes	98.2%	N/A
		SGM	94.4%	N/A
Sebe et al. (2004)	RGB	Bayesian network	99.4%	10%
Fu et al. (2004)	HSV	GMM	N/A	N/A
		Histogram	N/A	N/A
Phung et al. (2005)	YCbCr	Thresholding	82%	18.7%
	RGB	Bayes	88.9%	10%
	RGB	Multilayer perceptron	88.5%	10%
	YCbCr	SGM	88%	10%
	YCbCr	GMM	85.2%	10%
Ravichandran & Ananthi (2009)	CIE-Lab	k-means	N/A	N/A

Note: SGM – Single Gaussian model
SOM – Self organising map
BN – Bayesian network
N/A – Not applicable
GMM – Gaussian mixture model
NN – Neural network
PNN – Probabilistic NN

Colour Model

Colour is the brain's reaction to a specific visual stimulus. Colour can be described by measuring its spectral power distribution, i.e. the intensity of the visible electromagnetic radiation at many discrete wavelengths, which leads to a large degree of redundancy. The reason for this redundancy is that the eye's retina samples colour using only three sensitive bands, roughly corresponding to red, green, and blue light.

A colour model is a method by which colour can be specified, created, and visualised. A human defines a colour by its attributes of brightness, hue, and colourfulness. A computer describes a colour using amounts of red, green, and blue

Phosphor emission required to match a colour. A colour is usually specified using three co-ordinates or parameters. These parameters describe the position of the colour within the colour model used. Different colour models behave differently in different applications.

The choice of colour model can be considered as the primary step in skin colour detection modelling. Several colour models have been proposed in the literature for skin colour detection methods. Different researchers have used varying colour models for different reasons, for example, YCbCr colour model has been widely used since the skin pixels formed a compact cluster in the Cb-Cr plane (Albiol et al., 2000); HSV colour model has been used due to its close relation to human colour perception (Sobottka & Pitass, 1996); two components of RGB normalised colour model have been proposed to minimise luminance dependencies (Wang & Sung, 1999); and CIE-Luv has been used by Yang and Ahuja (1999) to reduce dependence of lighting condition. However, it is still not clear which colour models are best use for skin detection. Some literatures were confirmed that the use of a specific colour model can improve the performance of the skin colour classifier (Lee et al., 1996; Wang & Sung, 1999). However, according to Albiol et al. (2001) this is not exactly true because some skin colour distribution models have proven to be suitable for specific colour models. The colour model that is commonly being used in computer systems, television, and video is the RGB colour model.

An image can be described as a matrix of pixels, which could be in the form of monochromatic and chromatic image. This study focuses on the colour image. To date there are many type of colour models used by practitioners to describe the image. The most commonly colour model used for colour image is the RGB colour model. A RGB colour model can be described as a matrix with a size of m x n pixels with three colour channels, i.e. red, green and blue. It is a default colour model normally used for digital camera. Any other colour models can be computed from either a linear or a non-linear transformation from the RGB colour model.

According to Gomez and Morales (2002), the transformation of colour model from RGB into other colour model will reduce the overlap between skin and non-skin pixels. The transformation could also reduce problems caused by varying illumination conditions. Meanwhile, Yang and Lu (1998) found that skin colour differ more in intensity than in chrominance. Hence, it has been a common practice by many researchers to drop the luminance component for skin classification. However, Vezhnevet et al. (2003) argued that excluding colour luminance from the classification process will not lead to better skin and non-skin discrimination, but it could improve to generalise sparse training data and help construct skin classifier for images with different lighting intensity.

Skin colour detection is a very popular and useful technique for detecting and tracking human body parts, especially faces and hands. The use of skin colour detection techniques attract many researchers due to their high speed processing as well as their invariance to rotation, translation, scale, and partial occlusion (Vezhnevets et al., 2003; Kakumanu et al., 2007; Ghouzali et al., 2008). However, the most commonly used skin colour classification technique, i.e. pixel-based is not robust enough in dealing with complex environments (Ghouzali et al., 2008). Changing lighting conditions and complex background containing varying colour surfaces as well as objects with skin-like colours are major problems that limit its use in practical real-world applications. Many researchers do not provide strict justification of their colour model choice because acceptable skin detection results are possibly obtainable on limited dataset with almost any colour model. Some researchers

(Schumeyer & Barner, 1998; Yang et al., 1998; Storring et al., 1999; Yang & Ahuja, 1999) have provided justification for optimality of their choice for the skin model they employed. Some researchers (Zarit et al., 1999; Gomez, 2000; Terrillon et al., 2000; Gomez & Morales, 2002; Stern & Efros, 2002) have devoted to comparative analysis of difference colour models used for skin colour detection. For many colour model limitations, many researchers have chose most suitable colour model for their skin colour detection method. Therefore, different colour models have been employed for different skin colour distribution models such as RGB (Jones & Rehg, 1998, 1999, 2002a; Kovac et al., 2003a; Saleh, 2004), RGB normalised (Gomez & Morales, 2002), CIE-XYZ (Lee & Yoo, 2002), HSV (Tsekeridou & Pitas, 1998; Garcia & Tziritas, 1999), YCbCr (Chai & Ngan, 1999), YIQ (Brand & Mason, 2000), YES (Saber & Tekalp, 1998), CIE-XYZ (Chen & Chiang, 1997b; Wu et al., 1999; Brown et al., 2001), and CIE-LUV (Yang & Ahuja, 1999).

Some of colour models have been experimented by many researchers in skin detection literature with the aim of finding a suitable colour model where the skin colour is invariant to illumination changing conditions (Kakumanu et al., 2007). All these studies have been done because the researchers believed that the colour model plays an important role in the performance of skin colour distribution modelling (Fu et al., 2004). This is the reason why the choice of suitable colour model used in skin colour detection or modelling is extremely important. Regardless to any specific skin modelling method, it cannot provide the impression of how good is the colour model suited for skin modelling. This is due to different modelling methods which produced different retrieval results under different colour models (Vezhnevets et al., 2003). In other words, the choice of colour models directly affects the kind of classifiers that should be used.

Colour model can be divided into three categories (Plataniotis & Venetsanoupoulos, 2000) as follow:

i. Device-dependent colour model. The colour models are associated with input, processing, and output signal devices.
ii. Device-independent colour model. The colour models are used to specify colour signals independently of the characteristics of a given device or application.
iii. User-oriented colour model. The colour models are utilised as a bridge between the user and the hardware used to manipulate the colour information.

RGB colour model is a one of the colour model that widely used in skin colour detection system. This colour model is the most commonly used for storing and representing digital images. It is a device-independent colour model. As its name implies, the RGB colour model consists of three primary colours; red (R), green (G), and blue (B). It is originated from Cathode Ray Tube (CRT) display application when it is convenient to describe colour as a combination of three coloured rays (red, green, and blue). One main advantage of the RGB colour model is its simplicity and speed dealing with web images. In many cases skin colour detection can be done directly on pixel value without colour model conversion (Jones & Rehg, 2002b). However, RGB colour model could not provide a perceptual uniform because the R, G, and B components are highly correlated in terms of the mix between luminance and chrominance (Vezhnevets et al., 2003). The luminance of a given RGB pixel is a linear combination of the R, G, and B values. Therefore, changing the luminance of a given skin patch affects all R, G, and B components (Elgammal et al., 2009). In other words, the value of the RGB will differ based on the intensity of the illumination. Figure 2 illustrates the results of different skin image of different races under different illumination conditions (Elgammal et al., 2009). The skin colour clusters for different races were identified at different locations in RGB colour model. This is because the location of a given skin patch in the RGB colour model will change based on the intensity of the illumination under such patch was imaged. Furthermore, RGB colour model does not separate luminance and chrominance, and R, G, and B components are highly correlated. Figure 1 illustrates the RGB colour model.

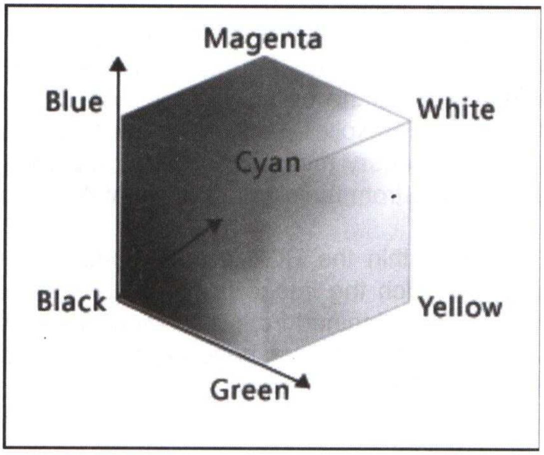


Figure 1: The RGB colour model

The RGB colour model is one of the most widely used colour model for processing and storing digital image data. It is also used for internet images. Vezhnevets et al. (2003) found that there is a high correlation between channels, significant perceptual non-uniformity mixing of chrominance and luminance data which has made the RGB not a very favourable choice for colour analysis and colour based recognition algorithms.

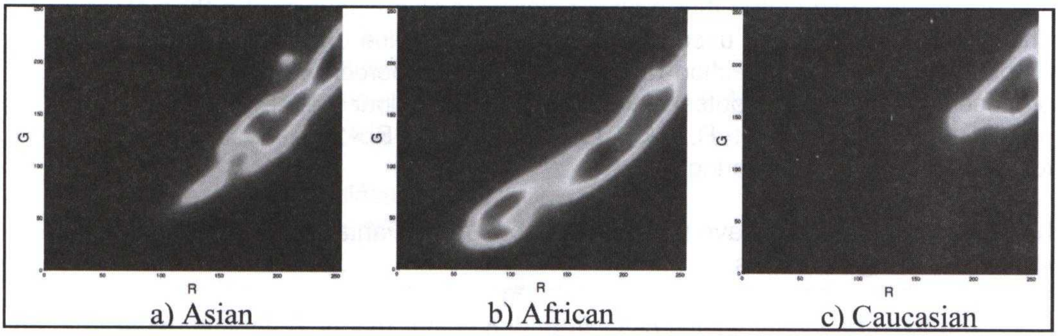


Figure 2: Density plots of Asian, African, and Caucasian skin in RGB colour model (Elgammal et al., 2009)

Despite the fundamental limitations aforementioned, the RGB colour model is extensively used in skin colour detection literature (Jones & Rehg, 1999; Brand & Mason, 2000; Hsu et al., 2002; Jedynak et al., 2002; Kovac et al., 2003b; Saleh, 2004; Phung et al., 2005). Among the main reasons is its simple and quite satisfying performance. It has also been used extensively in the detection of pornographic images (Zheng et al., 2004; Ruiz-Del-Solar et al., 2005; Kelly et al., 2008). This colour model has been used in this study.

Explicitly Defined Skin Region

The explicitly defined skin region is a one of skin colour detection methods. The explicitly defined skin region is a method to define explicitly the boundaries of skin cluster in some colour models. This method is often used and easily implemented into one or several channels of a colour model through a number of rules to decide whether a pixel belongs to skin colour or not. Brand and Mason (2000) constructed a simple one-dimensional skin colour classifier. A pixel is labelled as skin if some ratio between its R and G channels is between a lower and upper predefined bound. They have also experimented with one-dimensional threshold on IQ plane of YIQ colour model where I value is used for thresholding. The other methods explicitly define the skin colour in a two-dimensional colour model using elliptical boundary model (Lee & Yoo, 2002). The parameter of the elliptical boundary was estimated from the skin database at the training dataset.

Kovac et al. (2003a) worked within the RGB colour model and deal with the varying illumination conditions under which the image is captured. They classified skin colour by using heuristic rules that were obtained from two different conditions; uniform daylight and flash or lateral illumination. These rules have been used for pre-processing in face detection. They proposed the rules as follows:

i. Uniform daylight illumination:
   Pixel RGB is detected as skin if it meets the following criteria:
   $R > 95$ and $G > 40$ and $B > 20$ and $\mathrm{Max}(R, G, B) - \mathrm{Min}(R, G, B) > 15$ and $|R - G| > 15$ and $R > G$ and $R > B$
ii. Flashlight or daylight lateral illumination;
   Pixel RGB is detected as skin if it meets the following criteria:
   $R > 220$ and $G > 210$ and $B > 170$ and $|R - G| \leq 15$ and $B < R$ and $B < G$.

Saleh (2004) introduced a very simple rule for detecting a skin colour on RGB colour model. Saleh's rule stated that a pixel belongs to skin colour pixel if $20 < R - G < 80$. This simple rule has been used for pre-processing in face detection. By using this rule, he observed that skin detection rate is more than 96 percent. Meanwhile, Swift (2006) proposed opposite test to detect skin colour on RGB colour model. His rule stated that a pixel is not skin colour if $B > R$, $G < B$, $G > R$, $B < \frac{1}{4}R$ or $B > 200$. This rule has been used for pornographic image filtering.

Kamumanu et al. (2007) have summarised some disadvantages of explicitly defined skin region modelling as follows:

i. The fixed boundary values differ from one colour model to another, differ from one illumination to another and differ from different skin images database.
ii. It is very difficult to find a range of boundary value that covers all the pixels of different skin colour.
iii. It is less accurate in the case of shadows and situations where the skin colour is not distinguishable from background.
iv. The performance of skin colour detection is affected by the degree of overlap between skin and non-skin pixels of colour model.
v. It needs a very large training dataset to yield good skin detection rate because its inability to interpolate and generalise the data with small dataset.

In general, the currently available skin colour detection methods focus on several major issues; it is affected by the illumination changes, different colour models with the colour of cluttered background produces different detection result, and it could not discriminate between shadows and any other colour that are almost similar to skin colour. Furthermore, skin colours are different from different persons, races, or varying with age of the persons. From the literature, it can be concluded that by using a single colour feature alone, it is almost impossible to come up with a good skin colour distribution model.

METHODOLOGY

In general, the purpose of this study is to enhance a skin colour detection using RGB ratio that able to effectively and efficiently classify the skin and non-skin pixels. To achieve this objective, this section will be described the methodology which is divided in three main steps as follows:

i. Data preparation.
ii. Skin colour classifiers modelling, and
iii. Testing and evaluation.

Algorithm 1 describes in general the whole process that involved in skin colour detection system.

Algorithm 1: Skin colour classification modelling on pixel-based and region-based classification technique

```
Input: Skin image.
Output: Skin colour classifier.
Begin
Data preparation.
Data transformation from 3D to 2D format.
If (Region-based classification technique)
  Compute Colour mapping co-occurrence matrix (CMCM).
  Compute Haralick's texture features.
End If
Derive skin colour classifier
Measure skin colour classifier performance
End
```

Data Preparation

There are three steps have been involved in data preparation process; skin images collecting from websites, image segmentation and data transformation.

Skin Images Collecting

There are few skin data images available for public access such as Compaq dataset (Jones & Rehg, 1998), Sigal dataset (Sigal et al., 2004), Testing dataset for skin detection (TDSD) (Zhu et al., 2004), and db-skin dataset (Ruiz-Del-Solar & Verschae, 2006). Researchers such as Jones and Rehg (1998), Brand and Mason (2000), Brown et al. (2001), Jedynak et al. (2002), and Lee and Yoo (2002) used the Compaq dataset. This dataset consist of 6,818 annotated images. However, at this time of writing, the Compaq dataset is no longer available for public use (Ruiz-Del-Solar & Verschae, 2006). Thus, most researchers (Caetano et al., 2002; Kovac et al., 2003b; Saleh, 2004; Ruiz-Del-Solar & Verschae, 2006; Ravichandran & Ananthi, 2009) are using their own dataset.

The Sigal dataset which was developed by Sigal et al. (2004) is not suitable to use for skin colour detection algorithm development. This dataset does properly label skin and non-skin regions when labelling the ground truth frames (Ruiz-Del-Solar & Verschae, 2006). The TDSD dataset developed by Zhu et al. (2004) consists of 555 images (24 million skin pixels and 75 million non-skin pixels). This dataset consists of many images that are very unsatisfactorily annotated because its annotation process used a semi-automatic process for finding the skin and non-skin ground truth information (Ruiz-Del-Solar & Verschae, 2006). Ruiz-Del-Solar and Verschae (2006) classified the TDSD dataset images into three groups based on how accurate these images had been marked as skin and non-skin pixels areas, i.e. bad annotated images, good annotated images, and very good annotated images groups. Finally, the dataset called db-skin dataset from Universidal de Chile which consists of 93 still skin images and could be freely obtained via Internet and video images (Ruiz-Del-Solar & Verschae, 2006). These images were fully annotated by a human operator. They considered that these images are very difficult to manually segment between the skin and non-skin region because these images have either changing lighting conditions or complex backgrounds containing surfaces or objects with skin-like colours.

Based on limitation of the existing skin colour datasets as mentioned above such as:

i. Compaq dataset is not longer available, Sigal dataset is not suitable for skin colour distribution modelling,
ii. Only 100 skin images from TDSD dataset can be used for skin colour distribution modelling because most of skin images are unsatisfied annotation,
iii. Only 93 skin images can be obtained from UChile dataset, and
iv. The number of skin images mentioned in (ii) and (iii) are not enough to provide variation in skin colour tone and background colour variation.

Thus, there is a need to develop a new set of skin colour images with reasonable number of skin colour images that has variety of skin tone and background colour.
In this study, a new skin colour image database was developed called SIdb (Skin images database) consists of 357 skin colour images which is collected from Corbis website (Corbis, 2001) at the royalty free image section. The Corbis website provides a rich resource of skin and non-skin images suitable for content-based information retrieval. It should be noted that images from this website were also used as part of skin images collection by Jones and James (1998). These skin images were divided into two parts, namely a training dataset, which consists of 250 skin images and a testing dataset, which consists of 107 skin images. In other words, the ratio between the training set image and test set image is 70:30.

Throughout in this study, four skin images datasets were used, namely:

i. Training dataset that consists of 250 skin images. This dataset will be used to develop skin colour distribution model.
ii. Testing dataset that consists of 107 skin images. This dataset will be used to measure skin colour classifier performance.

iii. Benchmark image datasets. These datasets also will be used as comparison to measure the performance of skin colour classifier:

a. A TDSD dataset that consists of 100 very good annotated skin images (Zhu et al., 2004; Ruiz-Del-Solar & Verschae, 2006).
b. A UChile dataset that consists 93 skin images of db-skin dataset (Ruiz-Del-Solar & Verschae, 2006).

Image Segmentation

An accurate skin segmentation analysis is considered important in order to have images with the exact ground truth information and to get optimum result in skin detection experiment (Ruiz-Del-Solar & Verschae, 2006). It is difficult to obtain good annotated skin and non-skin pixels by using automatic or semi-automatic annotation. Hence, a fully human annotation should be employed.

Each of the images from SIdb was segmented manually using Adobe Photoshop software. This software is widely used for semiautomatic segmentation for anatomical structures in the Magnetic Resonance Images (MRI), Computerised Tomography, other medical images, and for skin and non-skin images segmentation (Zhu et al., 2004).

The Adobe Photoshop software is used under full human annotation. The regions of skin pixels were selected using the Magic Wand tool, which is available in Adobe Photoshop software. This tool enable user to select a consistently coloured area without having to trace its outline. This tool also allows user to interactively segment regions of skin by clicking the area needed. If contiguous area is selected, all adjacent pixels within the tolerance range within the colour region will be selected. The tolerance range defines on how similar in colour of a pixel within the region must be filled. Its value can be adjusted accordingly based on skin image, while regions of skin with complex shape can be segmented quickly. If the region of skin and non-skin are too difficult to segment because of almost skin and non-skin pixels are similar colour, then manual segmentation of skin and non-skin area using pen tracing tool is employed. By using this tool, the user needs to trace skin and non-skin area, manually. Figure 3 illustrates the skin and non-skin annotation to obtain ground truth skin and non-skin information. Meanwhile, Algorithm 2 describes the detail of skin and non-skin segmentation process.

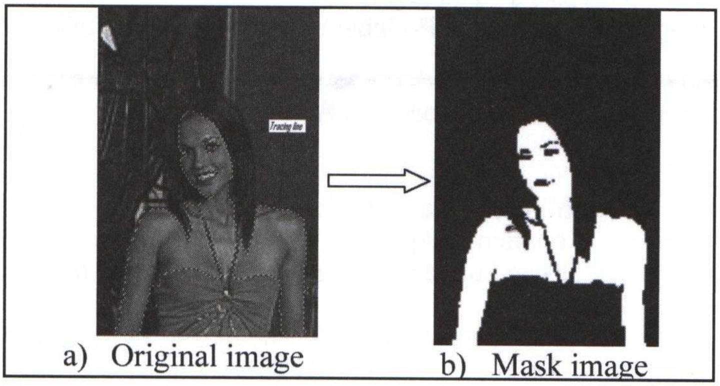


Figure 3: An annotation process for skin and non-skin ground truth information using Adobe Photoshop

Algorithm 2: Skin and Non-skin Segmentation

Input: Skin images Output: Mask images Begin For all images: Manually segment skin and non-skin area using Adobe Photoshop software. Assign skin area pixels value to [255 255 255] Assign skin area pixels value to [0 0 0] Save image (Mask image) in Portable Network Graphic (PBG) format End

This process has to be done carefully to exclude the eyes, hair, mouth opening, eyebrows, moustache and other materials covered on skin area. The RGB value of skin and non-skin areas were mapped to [255 255 255] and [0 0 0], respectively. This process produced a mask image (Figure 3(b)) and stored in Portable Network Graphics (PNG) format along with each original image that identifies its skin and non-skin pixels area.

Data Transformation

Before skin and non-skin pixels were used for experiments, each pixel of skin and non-skin portion were transformed into 2-dimensional matrix as illustrated in Figure 4. Meanwhile, Algorithm 3 describes the detail of data transformation process. This process involved collecting skin and non-skin pixels from skin images dataset. The collection pixels were done by matching them at corresponding location between original image and its mask image. Each of RGB value (in 3-dimesional matrix) will be transformed to 2-dimesional matrix and labelled as 1 or 0 to indicate whether the pixel belongs to skin or non-skin pixels, respectively.

Input: Skin images Output: Mask images Begin For all images: Manually segment skin and non-skin area using Adobe Photoshop software. Assign skin area pixels value to [255 255 255] Assign skin area pixels value to [0 0 0] Save image (Mask image) in Portable Network Graphic (PBG) format End

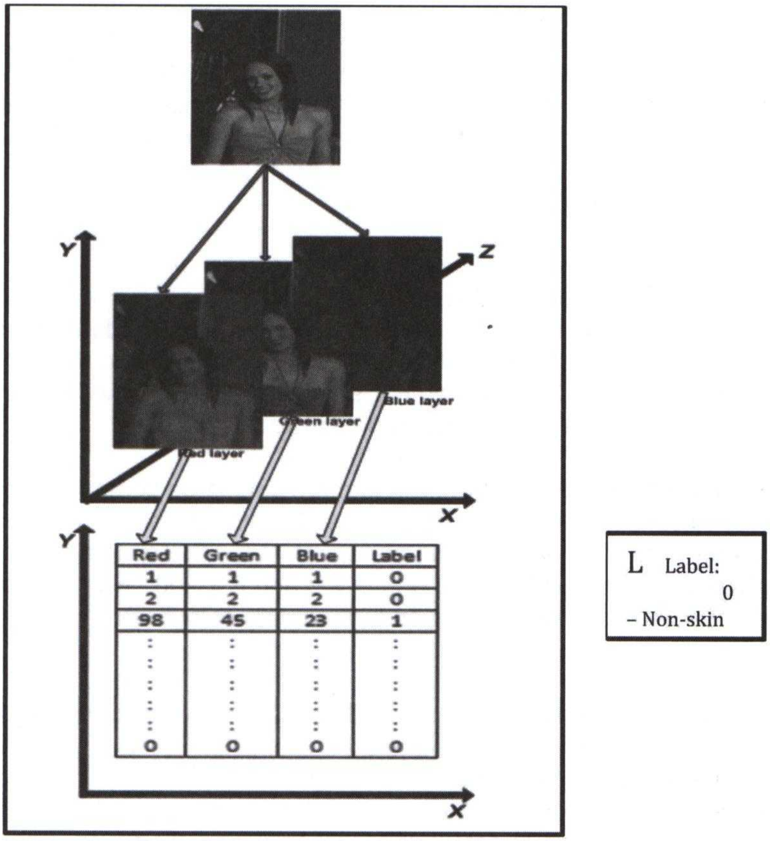


Figure 4: Transformation RGB colour model in 3-dimensional colour layer into 2-dimensional matrix

Skin Colour Classifier Modelling

Skin colour distribution modelling is a third step after the choice of colour model has been made and data transformation in skin colour detection algorithm development. In this study, a new technique called RGB ratio have been introduced.

RGB Ratio which proposed in this study is one of the explicitly defined skin region methods. RGB ratio will be formulated by examine and observation from histogram and scatter plot as well as from literature reviews.

Kovac et al. (2003b) developed a rule to detect skin colour on RGB colour model. This subsection will discuss and investigate the explicit method proposed by Kovac et al. (2003b), Swift (2006), and Saleh (2004) methods based on RGB colour model.

The Kovac rule (2003b) as described in Chapter 2 can be divided into four rules as follow:
Rule 1: $R > 95$ and $G > 40$ and $B > 20$ and

Rule 2: Max (R, G, B) – Min(R, G, B) > 15 and
Rule 3: lR – Gl > 15 and
Rule 4: R > G and R > B

This rule can be interpreted as the range of R value is from 96 to 255, the range of G value is from 41 to 239, and the range of B value is 21 to 254. Since R value is always greater than G and B, the second rule and third rule are always positive values, which can be rewritten as follow:

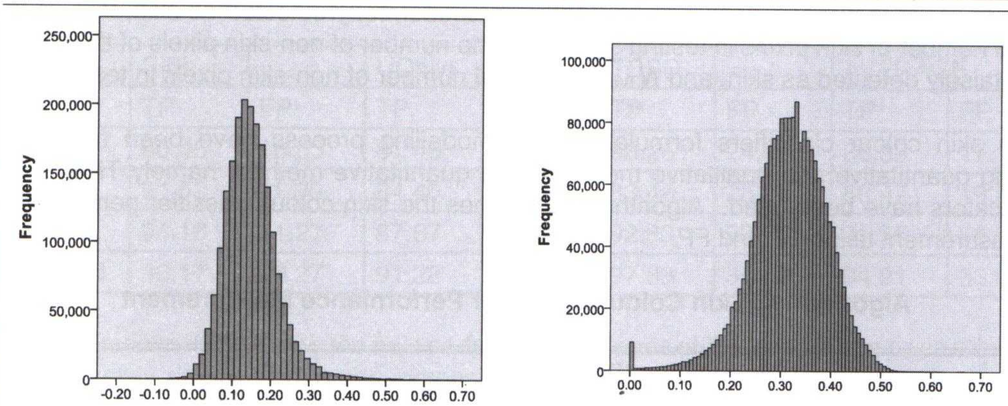
Rule 2: R – min(G, B) > 15
Rule 3: R – G > 15

Tomaz et al. (2003) described that if R-value is too high, and the G and B values are too low, it will result in a pixel is more to red, and should not be considered as skin pixel. In other cases when R < 100 and G < 100 and B < 100, it will result to dark colour that may be non-skin pixel, and when G > 150 and B < 90 or R + G > 400, it will result in yellow like colour. These conditions are not considered in Kovac's rule.

Swift (2006) rule as described in Chapter 2 is more simple as compared to Kovac's rule. The range of R-value is from 4 to 255, the range of B-value is from 1 to 200, and the range of G-value is from 1 to 255. It shows some agreement with Kovac's rule which is that a pixel is considered as skin pixel if R > G and R > B and B < 200. However, this rule is still unable to detect some dark skin colour and yellow like colour which is detected as skin colour.

Finally, a very simple rule was introduced by Saleh (2004) which consider only the value of R and G. This rule defines that a pixel is skin pixel when R – G is greater than 20 and less than 80. That means the range of R is from 21 to 255, while the range of G is from 0 to 234. This rule does not consider a present of B-value which contributed to the whitish colour. This rule is also unable to detect dark skin colour or skin cover under shadow, and yellow like colour and redder colour problems which is detected as skin pixel.
By considering the aforementioned issues, a new method has been developed based on painting colour concepts and colour ratio, which is based on colours mixing to produce new colour. This means some ratio of RGB has been taken to develop a new skin colour rule. The sum of R, G, and distance between R and G, and B values were observed based on ratio. The histogram of ratio of difference between R and G over the sum of R and G, and the ratio of B over sum of R and G are plotted from skin pixel of training dataset as shown in Figure 5. The new rule for skin colour have been developed based on histogram as follows:

$$\mathbf{0.0} \leq \frac{R-G}{R+G} \leq \mathbf{0.5 \text{ and }} \frac{B}{R+G} \leq \mathbf{0.5} \qquad \text{(Equation 1)}$$



(a) Histogram of $\dfrac{R-G}{R+G}$ (b) Histogram of $\dfrac{B}{R+G}$

Figure 5: Histogram of $\dfrac{R-G}{R+G}$ and $\dfrac{B}{R+G}$

The performance of classifier formulated from pixel-based classification technique have been compared to the skin distribution model introduced by Kovac et al. (2003b), Saleh (2004), and Swift (2006).

Testing and Evaluation

The performance of skin colour detection algorithm can be measured by two methods, i.e. quantitative and qualitative techniques (Vezhnevets et al., 2003). The quantitative method consists of two techniques, i.e. Receiver Operating Characteristics (ROC) and the true and false positive. Meanwhile, qualitative technique is based on observe the ability of skin colour classifier to classify skin and non-skin pixels from images. In this research, the ROC technique is not used as part of skin colour detection measurement, and will not discuss in the following paragraphs.

The true positive (TP) and false positive (FP) are statistical measures of the performance of a binary classification test. Binary classification is the task of classifying the members of a given set of objects into two groups on the basis of whether they have some property or not.

The TP is also called sensitivity, measures the proportion of actual positives, which are correctly identified as such. Meanwhile, FP measures the proportion of actual negative which are incorrectly identified. The FP rate is equal to the significance level. The specificity of the test is equal to one minus the FP rate (1 – FP). In case of skin colour detection, the performance of skin colour detection algorithm can be translated to following equation (Vezhnevets & Andreeva, 2005):

$$TP = \frac{I_{pos}}{N_{pos}} \qquad FP = \frac{I_{neg}}{N_{neg}}$$

where, I_{pos} is number of skin pixels of testing set correctly detected as skin, N_{pos} is the total number of skin pixels in testing set, I_{neg} is the number of non-skin pixels of the testing set falsely detected as skin, and N_{neg} is the total number of non-skin pixels in testing set.

The skin colour classifiers formulated from modelling process have been measured using quantitative and qualitative method. The quantitative method, namely TP and FP indicators have been used. Algorithm 4 describes the skin colour classifier performance measurement using TP and FP.

Algorithm 4: Skin Colour Classifier Performance Measurement

```
Input:    Pixels' features (Records).
Output:   True positive rate (TPR) and false positive rate (FPR).
Begin.
 N ← No. of skin records.
 M ← No. of non-skin records.
 TP ← 0
 FP ← 0
 For (each record)
Feed (record into skin colour classifier)
              If (detected as skin)
                         If (Label ==1)
                                    TP ← TP +1
                         Else
                                    FP ← FP + 1
                         End if
              End if
 Loop
TPR ← TP/N
FPR ← FP/M
End.
```

The performance of skin colour classifiers will be measured using testing dataset, SIdb and benchmark datasets, i.e. UChile and TDSD datasets. The average of performance for these three datasets have been used to indicate overall skin colour classifiers performance. Meanwhile, the qualitative method is measured based on the ability of classifier to detect skin and non-skin on a given skin image.

RESULTS AND DISCUSSION

The explicitly defined skin region method is the easiest and fastest method to define skin colour region. This method is always used as the first step to detect face (Kovac et al., 2003b), people and pornographic image (Kelly et al., 2008), etc.

Table 3 shows the performance of the proposed rules as compared to Kovac, Swift, and Saleh rules. Figure 6 illustrates some examples of qualitative result skin colour detection for these rules using qualitative measurement. The white colour indicates as skin pixel while black colour indicates a non-skin pixel.

Table 3: Performance of skin colour classifiers

Rule	SIdb		UChile		TDSD		AVERAGE	
	TP	FP	TP	FP	TP	FP	TP	FP
Kovac	90.46	10.53	81.46	16.76	93.25	24.19	88.39	17.16
Saleh	91.50	11.66	84.40	19.08	83.46	28.12	86.47	19.62
Swift	94.16	31.27	87.67	40.24	92.83	33.63	91.55	35.05
Proposed	96.17	26.27	91.22	37.84	97.33	35.09	94.91	33.07

The RGB ratio method shows the best performance in terms of TP value. It can be concluded that the newly proposed rule can increase the performance of skin colour detection with little big trade-off FP as compared to others.

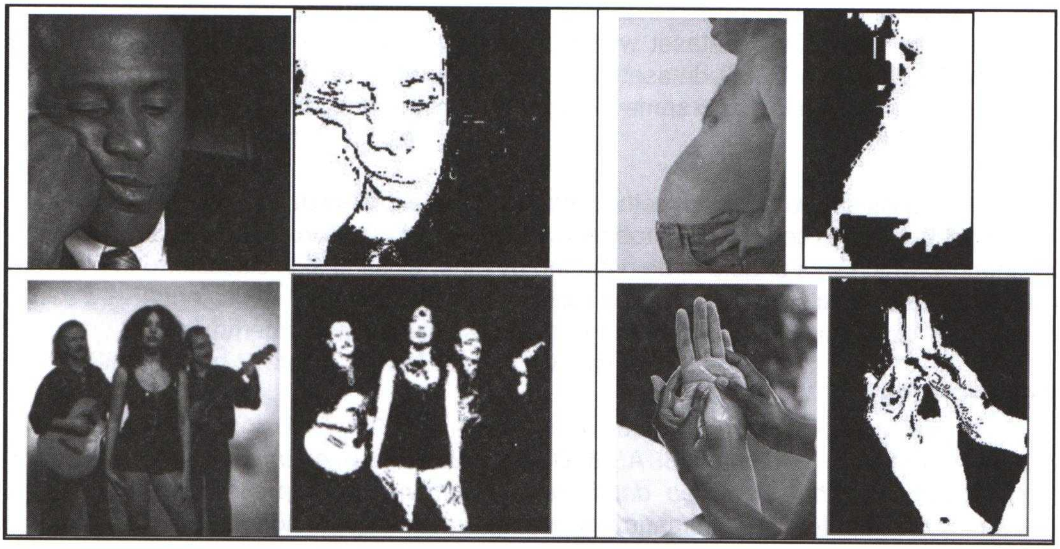


Figure 6: Examples of skin colour detection

CONCLUSION

Skin colour detection is a process to classify a desire pixel into skin or non-skin colour. The classification process can be carried out in two ways, namely pixel-based or region-based classification techniques. The pixel-based skin colour classification sometimes referred to as colour-based skin classification is popular among researchers because it is invariant to scale, occlusion, and rotation. However, one of the problems with pixel-based classification is high false positive (FP), which is a non-skin pixels detected as skin pixel due to similar colour (Kelly et al., 2008).

Most of the researchers developed skin colour detection model based on certain criteria of skin tone with control illumination condition. They used different skin image datasets for developing skin colour distribution model. The performances of skin colour classifiers are very encouraging for specific skin image dataset. Thus, it is not possible to obtain fair comparison between different methods or different modelling techniques used to classify skin and non-skin colour.

This study investigated and proposed skin colour distribution model based on pixel-based classification technique using RGB ratio method. The RGB ratio method is categorised as explicitly defined skin region method. This study has successfully achieved the stated objective.

The RGB ratio model has been compared to Kovac, Saleh, and Swift models and the experimental results showed that the RGB ratio model outperform all other techniques in term of TP. Besides using a SIdb dataset that has been developed in this study, the benchmark dataset have been used to test and validate the skin colour classifiers formulated in this study. The benchmark dataset used in this study is TDSD (Zhu et al., 2004) and UChile (Ruiz-Del-Solar & Verschae, 2006) datasets. The experimental results showed that the classifier formulated also able to detect skin and non-skin from these two benchmark datasets, which produce high true positive (TP) and low false positive (FP). The experimental results also showed that the performances of classifiers are slightly reduced when validate with TDSD dataset which provides slightly high FP. This phenomenon occurred because the TDSD dataset used semi-automatic method to segment skin and non-skin colour, which leads to some disturbances into non-skin colour (Ruiz-Del-Solar & Verschae, 2006).

The RGB ratio is a new modified method introduced to explicitly defined skin region model. This model is able to solve some problems related to darken skin colour and skin covered by shadow, which was unable to be detected by other existing skin classifiers. It also can reduce FP rate, which is contributed by reddish objects.

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