Skin Color Classification Using Color Mapping Co-occurrence Matrix

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ABSTRACT: *This paper presents a new technique for region-based skin color classification using texture features. Texture features were extracted from a new introduced technique called Color Mapping Co-occurrence Matrix (CMCM). Thirteen Haralick's texture features were extracted from CMCM at four directions and were used as input parameters for two skin color classifiers namely stepwise Linear Discriminant Analysis (LDA) and Multi-Layer Perceptron (MLP) Neural Network. The performance indicator of each skin color classifier is measured based on true positive rate and false positive rate. The experimental results showed that the skin color classifier using input features from [RGB] CMCM at direction (1, 0o) provides the most superior performances as compared to other CMCM's directions for both classifiers. It can also be concluded that MLP performs slightly better in classification performance as compared to stepwise LDA.*

Keywords: Skin Color Classification, Texture-based Classification, Color Mapping Co-occurrence Matrix, Region-based Classification, Texture Feature

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1. Introduction

Skin color detection is a process to determine whether a desired pixel or a group of pixels belongs to skin or non-skin color. In other words, skin color 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 presence of skin and non-skin can be determined by manipulating the color or texture of a pixel in an image. 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 categorized into two categories; pixel-based and region-based. Pixel-based skin color classification is carried out at pixel level where each pixel is classified separately based on its color properties. On the other hand, region-based skin color classification is carried out based on a group of pixels, where spatial arrangement of a group of pixel properties was taken into consideration. Skin color detection has been used for pre-processing in some application such as face detection [1, 2], pornographic filtering [3], etc.

The main challenge of skin color detection is to develop a classifier that is robust to the large variation in skin color appearances. This process is difficult because the appearance of a skin color in an image depends on the illumination conditions where the image was captured. Therefore, the main problem in skin color detection is to represent the skin color 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 color such as wood, leather, skin-colored clothing, hair and sand. Furthermore, skin color is different between races and can be different from a person to another, even with people of the same ethnicity. Finally, skin color will appear a little different when different types of camera were used to capture the object or scene.

The objective of this paper to develop a new skin color distribution modeling technique based on Haralick's texture features. These features have been extracted from Color Mapping Co-occurrence Matrix (CMCM) technique. The CMCM technique is an extension of gray level co-occurrence matrix (GLCM) technique which is introduced by Haralick et al. [4] to compute second order statistical texture features. The features computed from CMCM technique were used as input to the skin color classifier. Two types of classifiers were used; Linear Discriminant Analysis (LDA) [5] and Mult-Layer Perceptron Neural Network (MLPNN) [6]. The rest of this paper is organized as follows: Section 2.0 presents some background of this paper. Section 3.0 describes a proposed skin color classification technique used in this paper. Experimental results are presented in Section 4.0. Finally, the main conclusion is outlined in Section 5.0.

2. Background

Research in skin color modeling can be categorized as pixel-based and region-based. Starting from Jones and Rehg [7] till now, most of the researchers worked on the former technique [6]. This fact could be due to skin color is invariant in term of size and orientation [8]. Another reason for its popularity is pixel-based is simpler to compute and thus result in faster processing as compared to other methods [9]. A simple technique for skin detection modeling is to implement one or several thresholds [10-12] to decide either a pixel is skin or non-skin. A more advance modeling techniques such as neural networks [13], Bayesian Networks [14], maximum entropy [15] and *k*-means clustering [16] have also been used to detect skin color pixel. One of the main disadvantages of the pixels-based approaches is that the spatial distribution and local variation in color are ignored. Another problem with pixel-based approach is normally it has high false positive rate of non-skin regions due to similar color values of skin and non-skin pixel [17].

The region-based skin modeling technique is introduced to improve skin color detection by reducing the false positive rate. This technique uses spatial information of skin color pixels to improve detection rates. In other words, region-based skin modeling technique takes into account the relative position among pixels in a region of an image. Faliang et al. [18] introduced region-based algorithm for detecting skin color in a static image. They had chosen the Single Gaussian skin color model in the normalized RG space after analyzing the distribution of skin color in six different 2D chrominance spaces; RG normalized, TS, HS, CIE-ab, IQ, and CbCr. Images are first segmented into paths using an improved fuzzy *c*-means algorithm and initialized cluster centroid, then the percentage of skin color pixels in each patch were computed. According to the corresponding percentage, patches are classified as either skin color region or non-skin color region. They used a Receiver Operating Character (ROC) curve to analyze the performance of skin detection classifier with difference thresholds and found that the true detection rate is in the range between 75.2 percent to 92.3 percent with false detection rate is in the range between 23.9 percent to 38.1 percent.

Yang et al. [19] proposed skin detection algorithm by using geometric features of skin regions to effectively classify skin and non-skin pixels. In this method, a histogram technique has been used for skin color detection. Then, the contours of skin regions are constructed using a curve evolution method based on adaptive grids. Finally, the geometric features are extracted from the contours and the cosine similarity measure is adopted for skin color detection. Their experimental results have shown that the proposed method tested on faces, bikinis, and nude datasets performed well with skin detection rate of 93.5 percent and error rate of 6.2 percent.

Ghouzali et al. [20] proposed a skin color detection algorithm using a Discrete Cosine Transform (DCT). Their algorithm has been applied to a group of pixels at location that used a block-based feature vector which considers both color and texture information about skin's neighbors. The DCT coefficients are assumed to follow a generalized Gaussian distribution. The model parameters are estimated using the maximum-likelihood (ML) criterion applied to a set of training skin samples. The DCT of the neighborhood centered by each pixel is used to create the feature vector. For each pixel p, the DCT of a 3×3 block M_p centered on p is employed as the local region of pixels p. Subsequently, the DCT coefficients of each component block are computed separately; hue and saturation planes. To validate this technique, they used the Test Database for Skin Detection (TDSD) [21] with manually labeled ground truth with true positive of 97 percent and false positive of 30 percent, respectively.

Jiao [22] proposed a Gabor filter along with a Sobel edge operator to improve skin color detection. A Gabor filter is a band-pass filter that selects a certain wavelength range round a centre wavelength using Gaussian function. They found that the performance of skin detection rate increases when the Sobel edge and Gabor filter were applied as compared to pixel-based skin color classification. Meanwhile, Wang et al. [23] used a Gabor filter to train skin and non-skin texture features. They found that many non-skin pixels whose color information is similar to the skin are removed because their texture features are different from those of the skin region.

Finally, Cao et al. [24] have compared some techniques for skin color modeling such as invariant moment, color histogram, skin region statistics, and texture-based technique. They applied energy, contrast, correlation, and entropy properties as texture features in their experiments. They found that the performance of texture-based method is better as compared to invariant moment [25], color histogram [7], and skin region statistic [26]. Furthermore, they also proposed the combination of some weaker skin detection classifiers, which are built by the Learning Vector Quantization [27] based on color, shape, texture features with Adaboost method [28]. Adaboost is an adaptive algorithm to boost a sequence of classifiers. They also found that a combination skin color classifier performs better as compared to single skin color classifier. It should be noted that research that focused on region-based skin color detection is hardly found in the literature at present time. The fact is perhaps due to this method requires more processing time as compared to pixel-based method..

3. Methods

3.1 Skin Image Datasets

There are a few skin image datasets which are available for public access such as Compaq dataset [29], Sigal dataset [30], TDSD dataset [21], and UChile dataset [31]. The researchers in [29], [32], [33], [15], and [26] have used Compaq dataset in their experimental investigations. However, at this time of writing, the Compaq dataset is no longer available for public use [31]. Thus, some researchers [10, 11, 16, 31, 34] resorted to develop their own dataset as some other available skin datasets are not suitable to be used for skin color modeling.

The Sigal dataset does not take care the skin and non-skin regions properly when labeling the ground truth frames [31]. The TDSD dataset contains 100 skin color images and many images that are very unsatisfactorily annotated because its annotation process is based on semi-automatic process for finding the skin and non-skin ground truth information [31]. Finally, the dataset called UChile dataset from Universidad de Chile which contains only 93 still skin images and could be freely downloadable via Internet. The UChile dataset contains skin images that 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 of varying environmental conditions such as different lighting condition and involving complex background scenery. Based on the above mentioned scenario, there is an urgency to develop a new set of skin color images with a reasonable number of images that have variety of skin tones and background colors.

In this paper, a new skin color image database was developed called Skin images database (SIdb). SIdb consists of 357 skin color images which is collected from Corbis website [35] at the royalty free image section. The Corbis website provides a rich resource of skin and non-skin images suitable for content-based image retrieval. It should be noted that images from this website were also been used as part of skin images collection by Jones and James [29]. These skin images were divided into two parts; 70 percent images were used as training dataset, and 30 percent were used as testing dataset. It should be noted that TDSD dataset and UChile dataset have been used as benchmark datasets in this paper for comparison purpose.

3.2 Color Mapping Co-occurrence Matrix

Haralick et al. [4] proposed Gray Level Co-occurrence Matrix (GLCM) method to represent texture features in an image. In this method, the co-occurrence matrix is constructed based on the orientation, and distance, d as illustrated in Figure 1.

Similar to the concept of GLCM in computing texture features, this paper presents a new color mapping between the color bands of R, G and B. This method is an extension of the method proposed by Haralick et al [4] by projecting it to mapping between the band colors. This mapping process between the band colors will lead to four different matrices for skin portion and another four different matrices for non-skin portion for each skin. This matrix is called Color Mapping Matrix (CMM). The new Color Mapping

Co-occurrence Matrices (CMCMs) of each image were computed from these CMMs for skin and non-skin portion, separately. This color mapping were obtained for the distance of $d = 1$ and angle, ¸ from 0^o to 135^o. Thus, four directions have been tested for [RGB] CMCM; direction at $(1, 0^o)$, $(1, 45^o)$, $(1, 90^o)$, and $(1, 145^o)$.

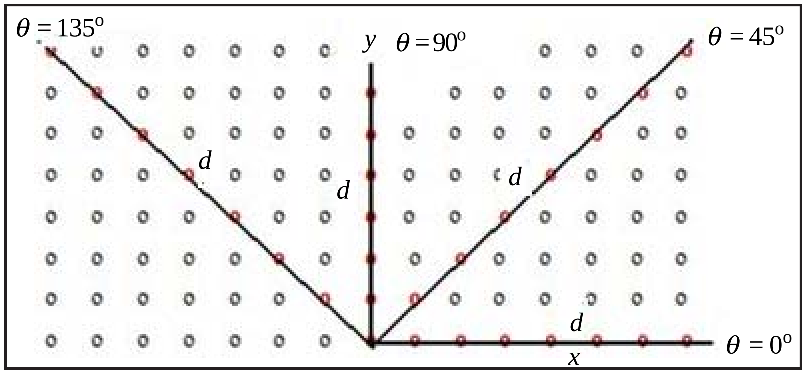

Figure 1: Gray level co-occurrence matrix with distance, *d* and four angles *θ*

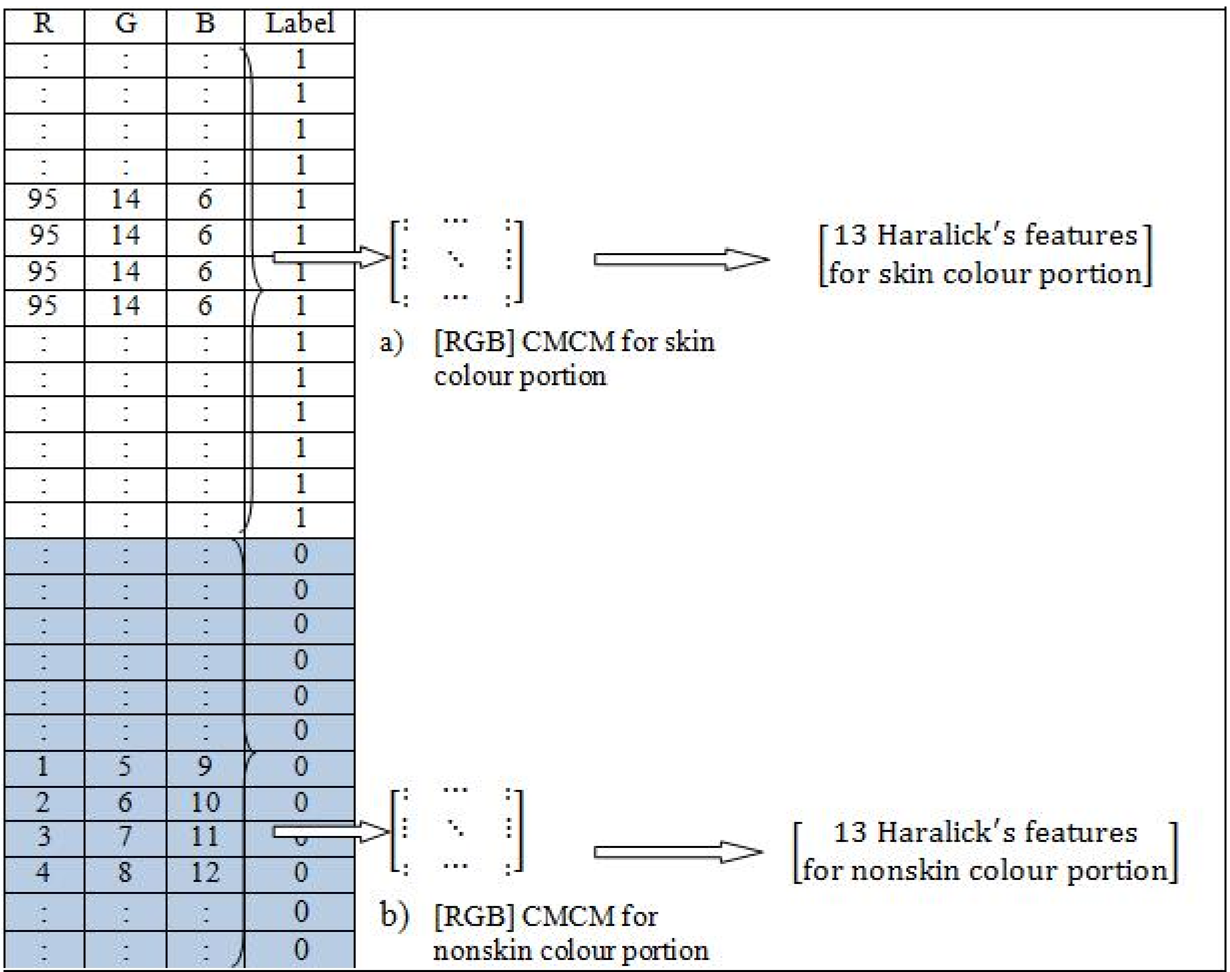

Figure 2. Illustration of the feature extraction process from skin and non-skin pixels for one image. (Note: R – Red; G – Green; B – Blue; CMCM – color mapping co-occurrence matrix)

Thirteen Haralick's features (Table 2) were computed for each matrix. Each image will produce two sets of thirteen texture features whereby one set for skin color portion and another set is for non-skin color portion. Figure 2 illustrates the example of how Haralick's features were computed from [RGB] CMCM matrix at $(1, 0^o)$. These texture features have been used as input in stepwise LDA.

3.3 Stepwise Procedure

The stepwise procedures are a common analytic procedure used in psychological and educational research to reduce the number of variables and to order variables in a given analysis [36]. It is most commonly employed in multiple regression and discriminant analysis. The goal of stepwise procedure is to sequence those variables (features) that maximize a criterion, which describes their ability to separate classes from one to another while at the same time keeping the individual classes as tightly clustered as possible.

The variables criterion used for variables selection is Wilks' Lambda, Λ can be defined as follows:

$$\Lambda = \frac{det\,(w\,(x))}{det\,(T\;(x))} \tag{1}$$

where $x = [x_1, x_2, x_3, ..., x_p]$ is a vector of the features that are currently included in the system. The W is the matrix of within-groups sum of squares and cross products for the features under consider is given by following equation:

$$W(i,j) = \sum_{g=1}^{q} \sum_{t=1}^{n_g} (x_{igt} - \bar{x}_{ig})\,(x_{jgt} - \bar{x}_{jg}) \tag{2}$$

The T is the matrix of total sum of squares and cross products is given by following equation:

$$T(i,j) = \sum_{g=1}^{q} \sum_{t=1}^{n_g} (x_{igt} - \bar{x}_{i})\,(x_{jgt} - \bar{x}_{j}) \tag{3}$$

where q is the number of classes, n_g is the number of samples in class g, $\bar{x}_{igt}$ is the value of feature i for sample t of class g, $\bar{x}_{igt}$ is the value of feature i for sample t of class g, $\bar{x}_{ig}$ is the mean of feature i over class g, and x_i is the mean of feature i over all classes, and $\bar{x}_j$ is the mean of feature j over all classes.

3.4 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a parametric technique to classify objects into mutually exclusive and exhaustive groups based on a set of measurable object's features. It is also often been referred to as pattern recognition, supervised learning, or supervised classification. LDA technique has been used when two or more population covariance matrices are equal [37]. It is based on assumption that each group follows multivariate normal (Gaussian) distribution. In general, discriminant analysis is a very useful tool for detecting the variables that allow to discriminate between different groups and for classifying cases into different groups with a better than chance accuracy. It has been widely used in many pattern recognition applications such as face recognition, speech recognition, fingerprint recognition, disease diagnosis, and business decision-making [38]. A stepwise procedure applied with LDA is called stepwise LDA.

3.5 Neural Network

Artificial Neural network (ANN) is a nonparametric method which has been studied since the middle of 30's, and it is proven as a powerful tool to solve problems in signal processing and pattern recognition fields [6, 39, 40]. ANN is an information processing paradigm that is inspired by the way biological neural systems process data [41]. Similar to human being, ANN learn by example. It is composed of a large number of highly interconnected processing neurons working in unison to solve specific problems.

ANN have the ability to learn complex data structures from a set of example patterns [42]. They have the advantage of working fast after the training phase even with large amount of data [43]. The multi-layer perceptrons (MLP) are perhaps the most popular type of ANN. A neuron consists of a set of input synapses, through which the input signals are received, a summing unit and an activation function. The input-output relationship is given by following formula:

$$\varphi(X) = f(\sum_{j=1}^{p} w_j x_j + \theta) = f(W^T X + \theta) \tag{4}$$

where W is the synaptic weight vector, X is the input vector, θ is a constant called a bias, $f(.)$ is the activation function, T is the transpose operator, and is the neuron output signal. The MLP architecture consists of input layer, followed by one or more hidden layers of neurons and $\varphi(X)$ an output layer.

Figure 3 illustrates the MLP architecture used for skin color modeling employed in this paper. The main reason for the selection of this ANN is, it has the ability to capture any nonlinear mappings to a specified accuracy [44]. Several researches have also shown that a three layer MLP is sufficient for most applications [45]. The value of input (x_i) can be the value of color model components or texture feature values and the output value (y_k) is whether skin (1) or non-skin (0).

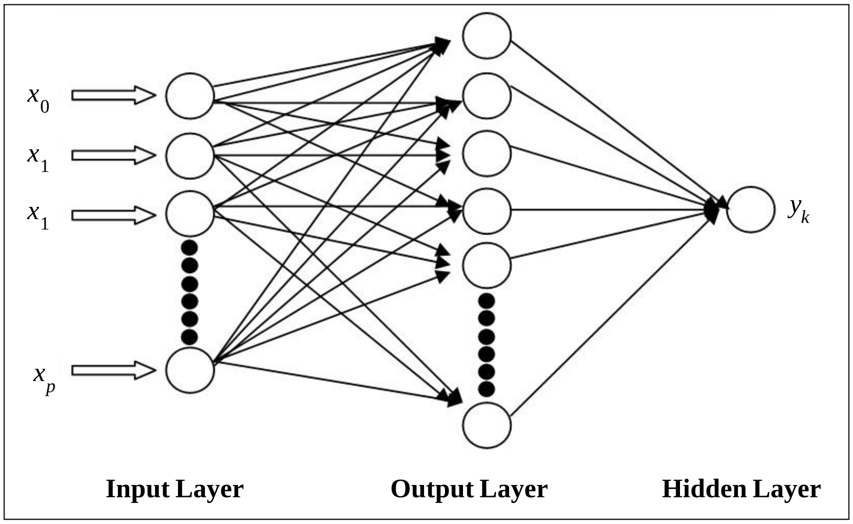

Figure 3. General MLP architecture for skin color modeling

During the training phase, the mean square error (MSE) difference between the network's target value and actual output value is computed to examine whether it has reached a criterion set. If the MSE criterion is met then the training is completed. If the MSE criterion is not met after some predetermined maximum epoch number, then it is necessary to stop training and starts new training by either increase or decrease the number of neurons in the hidden layer. In this paper, the MLP was trained using Levenberg-Marquardt learning algorithm [46].

The number of textures features used as input for MLP in this project is similar to the features that were used in stepwise LDA procedure. Table 1 summarized the parameters used in MLP skin modeling experiment.

[RGB] CMCM at Direction	Inputs	No. of nodes	Mean of MSE
(1, 0°)	IMC2, Correlation, Homogeneity, Energy, Difference entropy, and Sum average	10	2.9521 x 10^{-15}
(1, 45°)	Energy, Correlation, Homogeneity, Energy, Difference entropy and Sum average	10	1.3141 x 10^{-15}
(1, 90°)	Homogeneity, Energy, Correlation, Difference entropy, Sum entropy, Sum average and Sum of square: Variance	10	5.5755 c 10^{-6}
(1, 135°)	Energy, Homogeneity, Correlation, Difference entropy, Contrast and Sum average	10	7.2137 x 10^{-7}

Table 1. The summary of parameters used for MLP with 10-fold cross validation for [RGB] CMCM

3.6 Performance Measure

The performance of skin and non-skin color classification can be measured using true positive (TP) and false positive (FP) indicators. The TP and FP are statistical measures of the performance of a binary classification test. The TP and FP can be computed as follows:

$$TP = \frac{I_{pos}}{N_{pos}}, \quad FP = \frac{I_{neg}}{N_{neg}} \tag{5}$$

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

4. Result and Discussion

4.1 Linear Disriminant Analysis

Stepwise procedure was applied to Linear Discriminant Analysis (LDA) to choose a subset of textures, which is sequentially, identify those textures that maximize a criterion to separate two groups. The Wilks' lambda criterion is used for this purpose. The output of LDA is a linear equation which is called linear discriminant analysis function.

Table 2 lists the coefficients factor for each texture feature after stepwise LDA had been applied. Some of the textures properties were eliminated from the system and significant textures were listed with its coefficient factor. These coefficient factor values uniquely correlated for each texture features. The high value of coefficient means that the corresponding texture feature is more significant as compared to other texture features. The LDA equation function, *D* can be derived from coefficient factor. For example, the equation for [RGB] at direction (1, 0^o) can be written as follows:

$$\begin{aligned} D &= 0.002 * Contrast + 29{,}443 * Correllation + 17.073 * Energy - 19.891 * Homogenety \\ &+ 0.009 * Sum\ average - 3.520 * Difference\ entropy - 150.0162 * IMC2 + 130.815 \end{aligned} \tag{6}$$

Table 3 summarized the performance of discriminant function, namely skin color classifier. The average of true and false positive rate was used to compare classifiers performance between difference CMCM directions. Most of the results show that the performance of classifier formulated with [RGB] CMCM at direction (1,0^o) outperforms other skin color classification at other CMCM directions. Meanwhile, the performance skin color classifiers formulated with [RGB] CMCM at directions (1,45^o) and (1,135^o) is almost at similar rate. However, the classifier derived from direction (1, 90^o) is totally failed to classify skin and non-skin pixels**.**

4.2 Multi-Layer Perceptron Neural Network

The numbers of textures used as input for MLP were based on texture features listed in Table 1. The features selection procedure was applied to reduce the dimensionality of feature set thus leads to reduce training time. A 10-fold cross-validation procedure has been applied while measuring performance of each MLP in each experiment. The performance of MLP has been validated with SIdb dataset and other benchmark datasets, namely UChile and TDSD datasets.

The training phase has been carried out for the whole SIdb dataset. Table 4 shows the performance results of skin color classification that were derived from different CMCMs. Similarly as in stepwise LDA, the performance of MLP skin color classifier were measured based on average of TP and FP rate. The lowest FP with high TP will be considered as the best result [9].

As can be observed from Table 4, the performance of MLP skin color classifier is closed to each other in terms of TP rate values. However, based on FP rate values, the skin color classifier formulated with [RGB] CMCM at (1, 0^o) provide the most superior classification performance as compared to other CMCM's directions. Meanwhile, the MLP classifier formulated with [RGB] CMCM at direction (1, 90^o) is totally failed to detect skin and non-skin color. In this particular case, the average values of TP and FP rates are 0.74 percent and 8.83 percent, respectively. This means that texture features, which were computed from [RGB] CMCM at direction (1, 90^o) cannot represent skin and non-skin groups at all.

Feature	Direction			
	(1, 0^o)	(1, 45^o)	(1, 90^o)	(1, 135^o)
1. Contrast	0.002			-0.002
2. Correlation	29.443	-7.514	11.474	-21.376
3. Energy	17.073	-34.426	-16.323	-40.951
4. Entropy		0.825		
5. Homogeneity	-19.891	29.454	46.136	29.949
6. Sum of square: Variance			0.001	
7. Sum Average	0.009	-0.011	-0.083	-0.011
8. Sum Variance				
9. Sum Entropy			3.865	
10. Difference Variance				
11. Difference Entropy	-3.520	2.060	8.638	4.658
12. Information Measure of Correlation 1 (IMC1)				
13. Information Measure of Correlation 2 (IMC2)	-150.162	69.796	-55.243	87.501
Constant	130.815	-77.781	13.083	-82.741
Centroid : Skin	4.048	3.029	3.479	3.630
Non-skin	-4.048	-3.029	-3.479	-3.630

Table 2. The feature's coefficient factor of [RGB] CMCM

CMCM at Direction	SIdb		UChile		TDSD		AVERAGE	
	TP	FP	TP	FP	TP	FP	**TP**	**FP**
(1, 0^o)	100	0.56	98.28	7.42	99.30	3.50	**99.19**	**3.83**
(1, 45^o)	100	0.56	98.28	5.91	99.10	13.70	**99.13**	**6.72**
(1, 90^o)	0	1.90	0.22	17.96	2.00	5.10	**0.74**	**8.32**
(1, 135^o)	100	0.56	98.28	5.81	98.90	15.70	**99.06**	**7.36**

Table 4. The MLP classifier performance for [RGB] CMCMs

4. Conclusions

This paper presents a region-based skin color classification technique using LDA and MLP to model a skin color distribution. The region-based classification was carried out using texture features extracted from the newly introduced CMCM method at four directions. The number of texture features used as input to LDA and MLP is based on results obtained from the stepwise procedure that has been applied to the datasets using CMCM method.

It can be concluded that [RGB] CMCM at direction (1, 0^o) is the most superior as compared to [RGB] CMCM at direction (1, 45^o) and (1, 135^o). Meanwhile, [RGB] CMCM at direction (1, 90^o) totally cannot be used to model a skin color distribution because it provides a very low TP rate in both cases; LDA and MLP. Other experimental results shows almost similar consistent trends of classification performances between LDA and MLP skin color classifiers. The performance of MLP not significantly better than LDA in term of TP. This means that whether parametric (LDA) or nonparametric method (MLP) were used to model skin color distribution, it is not the main factor that contributes to robust skin color classification. The main factor is on how the raw image data is being pre-processed before being used as input in skin color modeling. The CMCM technique proposed in computing a skin texture features paved a new way for skin color classification and modeling.

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