DEVELOPMENT OF HUMAN SKIN DETECTION ALGORITHM USING MULTILAYER PERCEPTRON NEURAL NETWORK AND CLUSTERING METHOD

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by

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LIST OF ABBREVIATIONS

AC	Accuracy
ANNs	Artificial Neural Networks
BIOID	Biometric Identification Dataset
BMM	Beta Mixture Models
BP	Back-Propagation
BP ANN	Back- Propagation Artificial Neural Network
DE	Differential Evolution
DR	Detection Rate
EBPTA	Error Back Propagation Training Algorithm
ECU	Edith Cowan University
EM	Expectation Maximization
FA	False Acceptance
FNR	False Negative Rate
FPR	False Positive Ratios
FPR	False Positive Rate
GMM	Gaussian Mixture Model
I/O	Input / Output
LMS	Long, Medium and Short
LUT	Normalized Lookup Table
MLP ANN	Multilayer Perceptron Artificial Neural Network
MoG	Mixture of Gaussian
MSE	Mean Square Error
P	Precision
PCNN	Pulse Coupled Neural Network

RGB	Red Green Blue
SGM	Single Gaussian Model
SOM	Self Organizing Map
SPM	Skin Probability Map
th	Threshold
TPR	True Positive Ratios

PEMBANGUNAN ALGORITMA PENGESANAN KULIT MANUSIA MENGGUNAKAN RANGKAIAN NEURAL PERCEPTRON BERBILANG LAPISAN DAN KAEDAH PENGELOMPOKAN

ABSTRAK

Pengesanan kulit manusia merupakan langkah pra-pemprosesan yang penting dalam pelbagai aplikasi yang melibatkan imej seperti pengesanan wajah, pengesanan isyarat dan pengesanan bogel. Warna adalah sumber maklumat yang penting untuk pengesanan kulit manusia, dan beberapa kajian telah membincangkan kesan ruang warna ke atas pengesanan kulit. walan bagaimanapun, masih tiada kata sepakat ke atas ruang warna yang paling sesuai untuk pengesanan warna kulit. Tambahan pula, prestasi yang baik oleh aplikasi-aplikasi berkenaan bergantung kepada pengelas kulit yang boleh dipercayai, yang sepatutnya boleh membezakan piksel kulit dan bukan kulit untuk pelbagai jenis orang tanpa mengira umur, jantina dan kaum. Pelbagai pengelas termasuk pengelas pintar telah digunakan untuk pengesanan kulit manusia dengan kelemahan tersendiri seperti ketepatan yang rendah. Dalam kerja ini, satu kajian perbandingan menyeluruh menggunakan Rangkaian Neural Buatan Perceptron Berbilang Lapisan (MLP ANN) telah dijalankan ke atas pelbagai ruang warna (RGB, RGB ternormal, YCbCr, YIQ, HSV, YUV, YDbDr, dan CIE L*a*b) bagi menentukan ruang warna yang paling optimum. Tambahan pula, kesan menggabungkan maklumat tekstur dengan maklumat warna telah dikaji bertujuan untuk meningkatkan prestasi pengelas kulit. Algoritma Evolusi Berbeza (DE) digunakan dalam kerja ini untuk memilih maklumat warna dan tekstur yang optimum untuk mencapai tindak balas yang optimum. Keputusan eksperimen menunjukkan

bahawa ruang warna YIQ memberikan pemisahan yang ketara di antara piksel kulit dan bukan kulit, bagi ruang-ruang warna yang berbeza yang diuji menggunakan ciri-ciri warna. Tambahan pula, keputusan yang diperolehi juga mendedahkan bahawa penggabungan warna dan ciri tekstur menjurus kepada pengesanan kulit yang lebih tepat dan efisien. Berdasarkan keputusan pengekstrakan ciri ini, satu sistem hibrid berasaskan penggabungan MLP ANN dan kaedah pengelompokan *K-means* yang menggunakan ruang warna YIQ dan ciri statistik kulit manusia sebagai masukan telah dibangunkan untuk pengesanan kulit manusia. Prestasi sistem yang dibangunkan telah dibandingkan dengan sistem-sistem pengesan kulit pintar sedia ada. Keputusan eksperimen menunjukkan bahawa algoritma yang dibangunkan ini mampu mencapai ketepatan 87.82% pengukur-F1 berdasarkan imej-imej daripada pangkalan data ECU. Ini menunjukkan bahawa pemilihan ciri optima dan sistem pintar gabungan ini mampu mempertingkatkan ketepatan dan kebolehpercayaaan pengesanan kulit manusia secara ketara.

DEVELOPMENT OF HUMAN SKIN DETECTION ALGORITHM USING MULTILAYER PERCEPTRON NEURAL NETWORK AND CLUSTERING METHOD

ABSTRACT

Human skin detection is an important preprocessing step in many applications involving images such as face detection, gesture tracking, and nudity detection. Color is a significant source of information for human skin detection, and some studies have discussed the effect of color space on skin detection. However, there is no consensus on which color space is the most appropriate for skin color detection. In addition, good performance of such applications depends on reliable skin classifiers that must be able to discriminate between skin and non-skin pixels for a wide range of people, regardless of age, gender, or race. Many classifiers including intelligent classifiers have been utilized for human skin detection with a few limitations such as low accuracy. In this work, a comprehensive comparative study using the Multilayer Perceptron Artificial Neural Network (MLP ANN) is performed on various color spaces (RGB, normalized RGB, YCbCr, YIQ, HSV, YUV, YDbDr, and CIE L*a*b) to determine the optimum color space. Additionally, the effect of combining texture information with color information is investigated with the aim of boosting the performance of skin classifiers. The Differential Evolution Algorithm (DE) is used in this work to select the optimum color and texture information to achieve the optimum response. The experimental results show that the YIQ color space yields the highest separability between skin and non-skin pixels among the different color spaces tested using color features. In addition, the results reveal that combining color and texture features leads to more accurate and efficient skin detection. Based on these feature extraction results, a system based on a combination of an MLP ANN and k-means clustering which employs the YIQ color space and the statistical features of human skin as inputs is developed for human skin detection. The performance of the developed system has been compared with the existing intelligent skin detection systems. The experimental results reveal that the developed algorithm is able to achieve an accuracy of 87.82% F1-measure based on images from the ECU database. This result demonstrates that optimum feature selection and combination intelligent system are able to enhance the accuracy and reliability of human skin detection significantly.

CHAPTER ONE

INTRODUCTION

1.1 Background

Separating an image that consists of groups of identical linked pixels into regions is an image processing stage called image segmentation. The homogeneity of a region can be defined by various properties such as color, gray levels, and texture, among other factors (Liu & Chung, 2011). Skin detection is a good example of image segmentation, which can be accomplished by classifying image pixels appropriately as skin or non-skin pixels (Kakumanu et al., 2007) based on skin color. The importance of skin color detection comes from its use as a primary operation in many applications, such as face detection (Zhipeng, 2010; Harvir & Shaveta, 2017; Rakshit et al., 2017), objectionable content filtering (Lee et al., 2007), content-based image retrieval (Kruppa et al., 2002), medical imaging (Silveira et al., 2009; Castillejos et al., 2012), image coding (Choi et al., 2009), surveillance systems (Zhang et al., 2009; Ashwini & Meenu, 2017), Internet pornographic image filtering (Lee et al., 2010) and gesture analysis (Han et al., 2009). For example, face detection is accomplished by removing joint facial characteristics and employing skin color detection as a primary step to specify the face area. As a result, accurate and fast face detection can be accomplished.

Skin color is a robust cue in human skin detection. It has been widely used in various human-related image-processing applications. To use skin color information, many studies have focused on understanding its characteristics. Research analysis has shown that human skin color has a restricted range of hues and is not deeply saturated because the appearance of skin is formed by a combination of blood (red) and melanin (brown and yellow) (Fleck et al., 1996; Talukder et al., 2013). Therefore, human skin color does not fall randomly in a given color space but instead clusters within a small area in the color space. Several studies have shown that the major difference in skin color among different people lies largely in their intensity rather than in their chrominance (Waibel, 1996; Vandana et al., 2013; Zakaria et al., 2009). Thus, if an image is initially converted into a color space, which provides a separation of luminance channel and two chrominance components such as the normalized (r, g, b) color space, then skin-like regions can easily be detected (Chen et al., 2002).

1.2 Motivation and Problem Statement

Skin color information has recently gained attention for use in skin detection based on images. Skin color detection can be a very challenging task because the skin color in an image is sensitive to various factors such as illumination conditions, camera characteristics and ethnicity (Kakumanu et al., 2007). Numerous algorithms have been proposed for skin detection over the past several years.

The existing skin detection algorithms can be classified into four categories namely explicit skin cluster classifier, parametric classifiers, non-parametric classifiers, and adaptive/dynamic classifiers (Kakumanu et al., 2007, Vezhnevets & Andreeva, 2003, Abdullah-Al-Wadud et al., 2008). The first three are static-based. The explicit skin cluster classifiers, which are the simplest and most often applied methods, define the boundaries of the skin cluster in certain color spaces using a set of fixed skin thresholds (Chi et al., 2006, Gasparini & Schettini, 2006, Vezhnevets & Andreeva, 2003, Shi & Sun, 1999). Although such techniques are straightforward and can be used without any prior training phase, they lack flexibility in that other i.e. different imaging conditions could not be employed. This may result in the inaccurate detection of pixels (Al-Wadud et al., 2008).

The parametric classifiers can be based on a single Gaussian model (Almohair et al., 2007, Abdel-Mottaleb et al., 2002), a mixture of Gaussian (MoG) models (Kamata, 2010, Mohamed et al., 2008, Hossain et al., 2012), multiple Gaussian clusters (Phung et al., 2002), or an elliptic boundary model (Kwolek, 2003). However, the classification speeds of these classifiers are generally very slow because they must process every image pixel individually. They are also very slow when integrated into an ANN training phase (Lee & Yoo, 2002). Another drawback of these techniques is their inaccuracy of detection because they depend on approximated parameters rather than the actual distribution of skin colors (Al-Wadud et al., 2008). Moreover, their performances are inconsistent, depending significantly on the type of color space used (Vezhnevets & Andreeva, 2003).

The non-parametric classifiers estimate the skin color distribution based on a histogram of training images without deriving an explicit model of the skin color (Khan et al., 2011; Shahreza & Mousavi, 2008). This technique estimates a statistical model of the distribution of skin color by training the classifier with a set of training data. There are two advantages of this approach: its quickness in training and usage and its independence of the shape of skin distribution (Vezhnevets & Andreeva, 2003). However, such statistical models are insufficiently accurate due to the need for an infinite amount of training data. The adaptive or dynamic non parametric classifiers includes ANN-based methods. ANN have been used to solve a wide variety of tasks, like computer vision and speech recognition, that are hard to solve using ordinary rule-based programming. To the best of our knowledge, only a few human skin detection algorithms are based on ANNs, such as from the works of (Chen et al. 2002; Yang et al. 2010; Zaidan et al. 2010; Bhoyar & Kakde 2010; and Doukim et al. 2010). The limitations of these methods are discussed in the literature review (Chapter 2) and highlighted in Table 2.2.

Based on the brief discussion, the main problems of current skin-color detection techniques can be summarized as follows:

1. A common research result obtained on the effect of color space on skin detection is that different modeling methods react very differently to a color space change (Kakumanu et al. 2007; Vezhnevets & Andreeva 2003). Hence, one important question that remains unanswered is, “what is the best color space for skin detection?” Moreover, there has been no comprehensive study performed using ANNs to investigate and answer this important question in the skin detection field.
2. Some studies on human skin detection used texture information in addition to color information (Taqa & Jalab, 2010; Al Abbadi et al., 2013), but their selection for the combination of color-texture information was made based on their own preference. There is no solid justification for those specific selections.
3. Skin detection in digital images can be considered as a classification problem in which each image pixel of a dataset is classified into either skin pixels or

non-skin pixels. The ratio of skin pixels to the total number of pixels in an image differs from one image to another. This variation makes the associated image dataset imbalanced because the number of skin pixels does not equal to the number of non-skin pixels. Hence, measuring detection accuracy as the total number of predictions that were correct might not be an adequate performance measure because the class sizes are imbalanced. This problem was highlighted in the work of Santra & Christy (2012) and Chawla (2005). Hence, suitable performance metrics such as F1-measure should be used to measure the accuracy of skin detection in such cases to avoid bias.

4. The current skin color modeling techniques have crucial disadvantages such as low accuracy. The work of Abdullah-Al-Wadud et al. (2008), Kakumanu et al. (2007), Vezhnevets & Andreeva (2003), Chen et al. (2002), Zhang et al. (2004), Elgammal et al. (2001) and Marwala (2005) explained the disadvantages of the current techniques. More details are explained in Chapter2.

From the above discussion, it is clear that many human skin classification techniques have been proposed in this area but they still lack accuracy and efficiency. The flexibility of ANNs makes them a good choice to overcome these issues. When pursuing a reliable human skin detection system that incorporates skin information as input together with an ANN as a classification method, several questions can be raised:

1- How can one identify the best color space that can be used to represent skin as input to an ANN-based human skin detection system?

2- Is skin color information by itself sufficient for a reliable ANN-based skin detection system?

3- Can skin texture improve the accuracy of detection? If yes, what is the best combination of color-texture that can be used as input to the ANN-based skin detection system?

4- What is the best manner to convert the output of the ANN into a masking image that can identify skin and non-skin pixels?

In order to answer these questions, an investigation towards the development of simple but more efficient skin detector deems necessary.

1.3 Research Objectives

Following the limitations and problems discussed in Section 1.2, this research focuses on developing an ANN-based skin color detection technique that improves the accuracy of human skin detection in color images. To achieve the stated purpose, the objectives of the work are as follows:

1. To determine the optimal color space for human skin detection.
2. To determine the best color-texture combination using differential evolution algorithm.
3. To use an appropriate performance metric to measure the accuracy of skin detection.
4. To develop a combined ANN and the k-means clustering system for human skin detection.

1.4 Research Scope

This study uses an ANN and clustering method to develop a system for human skin color detection. In the quest of the development, a number of scope have been