COLOUR SPACES STUDY FOR SKIN COLOUR DETECTION IN FACE RECOGNITION SYSTEMS

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Abstract: In this paper we show the results of a work where a comparison among different colour spaces is done in order to know which one is better for human skin colour detection in face detection systems. Our motivation to do this study is that there is not a common opinion about which colour space is the best choice to find skin colour in an image. This is important because most of face detectors use skin colour to detect the face in a picture or a video. We have done a study using 10 different colour spaces (RGB, CMY, YUV, YIQ, YCbCr, YPbPr, YCgCr, YDbDr, HSV –or HSI– and CIE-XYZ). To make the comparisons we have used truth images of 15 different people, comparing at pixel level the number of correct detections (false negatives and false positives) for each colour space.

1 INTRODUCTION

The automatic processing of images containing faces is essential in lots of fields in our days. One of the most successful and important applications are face recognition systems (Zhao, 2003). The first stage in every face recognition system consists in the detection of the face from the image where it is included. There are several methods for finding a face in an image (Yang, 2002). In this study we are going to focus on a method classified into feature invariant approaches. This method consists in finding *human skin colour* to detect faces in pictures. In the bibliography there are many colour spaces that have been used to label pixels as skin. For example, there are studies using *RGB* (Naseem, 2005), *HSV* (Sigal, 2004), *YCbCr* (Jinfeng, 2004), *YPbPr* (Campadelli, 2005), *YUV* (Runsheng, 2006), *YIQ* (Jinfeng, 2004), etc. and even combinations of various colour spaces to solve the same problem together (Jinfeng, 2004).

The motivation for our study is that there is not a common criterion about which colour space is the best to find skin colour in an image. It is true that there are other studies that compare the behaviour of different colour spaces finding skin (Albiol, 2001), (Phung, 2005), but the approach of our study is completely different. We carry out a detailed study of how good are different colour spaces using the same parameters (the same images and the same method to find skin colour) and with high precision in comparisons, because we do the study *at pixel level*, using truth images. So, after the study we can state which colour space is better, and in what quantity, comparing the results of how many skin pixels we could identify using that colour format.

To explain our study, this paper has been organized as follows: section 2 provides a detailed description of the experiments performed. Results obtained are expounded and analysed in section 3. Finally, conclusions are explained in section 4.

2 EXPERIMENTS

We have studied in depth 10 different colour spaces (RGB, CMY, YUV, YIQ, YPbPr, YCbCr, YCgCr, YDbDr, HSV and CIE-XYZ) using 15 images, of different people, which are included in AR face database (Martinez, 1998).

To determine which colour space detects better the human skin colour we have generated the truth images of the 15 pictures used in the experiments. In these images, the parts of the photo which do not include skin colour are removed. So, in the truth

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images there are no hair, no beard, no lips, no eyes, no background, etc. Figure 1 shows two of the real images used in the study and the truth images for those pictures. For doing the classification, we have developed a K-Means classifier (Shapiro, 2001) with some improvements.

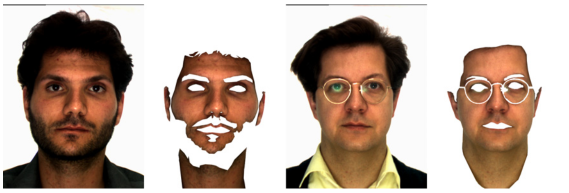

Figure 1: Example of two of the images (and the truth images for each) used in the study.

K-Means method is a clustering algorithm which groups into K classes the data to classify. In our case, these data are the pixels of the image. It is necessary to establish the value for K before the execution of the algorithm. We did some tests with different K values (K=2, K=3, K=4, K=7), as we can observe in figure 2, but at the end we decided to use K=3 in our study because we wanted a balance between performance and results quality. K-Means is a very efficient algorithm, but when K is increased, convergence time increases too.

Figure 2: Results obtained with K-Means algorithm used over RGB colour space when K = 2; K = 3; K = 4 and K = 7 (from left to right).

Moreover, we think that 3 classes are a very sensible choice for the type of images that we manage in our study (face recognition typical images with a constant background). In this case one class is associated to skin colour, another class groups the darkest parts of the image (which are mainly hair, beard, eyebrows…) and a third class is associated with the brightest parts in the image (such as the background and maybe some highlights in some parts of the skin).

For each colour space we have done tests with each channel alone, using two channels together (with all different combinations) and with the three channels of the colour space to discover which combination gives us the best results. As we said in the introduction section, we do the study at level pixel. Once K-Means method provides us the classification for pixels in a concrete colour space, we compare this classification with the truth image. The comparison is done for each pixel of the obtained result and the same pixel in the truth image. If the result obtained by the classifier coincides with what the truth image says for that pixel, we have a right detection, if our classier says that there is skin in a pixel where there is not, we have a false positive and finally if our classifier says that there is no skin in a pixel where really there is, we have a false negative.

Table 1 shows the right detection results for each colour space. As we can see, we have focused on the three channels of the colour spaces separately and in the three channels all together. When we use the three channels all together we have considered what most channels say (e.g.: if two of the three channels say that there is a hit in a concrete pixel, the final result is a hit).

3 RESULTS ANALYSIS

In this section we analyse and explain the results obtained in each colour space for skin detection. To obtain some theoretical support about the different colour models which are used, see biographical references (Shapiro, 2001) and (Pratt, 2001). Due to the number of pages of this paper, we are forced to summarise the results obtained in our study through table 1 (right detections rate).

3.1 RGB Model

This colour model is not very robust when there are changes in the illumination of the images. This explains why the channel which had more hits was the G channel when obviously the more important channel to find skin colour is R. The worse results in this model were naturally obtained by B channel. We can conclude that this colour space is not the most appropriate one to find skin colour in an image, although it is possible to use it with success if the environment (illumination) is constant.

3.2 CMY Model

This colour space obtains the worse results in the study. This fact is quite reasonable because its usage is specified for other fields (printing more than processing). Taking into account that this colour space is quite similar to RGB, it is normal that the best channel was M (because in RGB was G), just for the same reasons.

Table 1: Right detections for each colour space using the three channels of the space separately and the three together.

	RGB	CMY	YUV	YIQ	YCbCr	YPbPr	YCgCr	YDbDr	HSV	XYZ
C1	82.79%	82.86%	84.69%	84.69%	87.06%	84.69%	88.95%	88.95%	72.16%	87.44%
C2	87.23%	86.6%	87.86%	89.93%	87.86%	87.85%	87.48%	90.58%	94.04%	85.12%
C3	79.75%	82.33%	90.19%	70.32%	90.19%	90.19%	93.19%	91.42%	82.08%	74.1%
C1C2C3	86.55%	86.15%	89.7%	86.93%	89.8%	89.7%	92.63%	92.29%	95.06%	86.27%

3.3 YUV Model

The third channel of this colour space gives us quite good results (90.19% of right detections). V channel saves the information for the difference between the red component of the colour and the luminance. In this colour space, like in most of the followings, luminance information is separated from chrominance information, so the results obtained are better than for RGB model because they are more robust to brightness variations.

3.4 YIQ Model

Our conclusion for this colour space is that although it obtains acceptable results, YUV model, which is very similar, obtains better results. Therefore, according to our study, it is better to use YUV colour space than YIQ in skin detection.

3.5 YCbCr Model

This colour model is very similar to YUV. We can state that this colour space obtains quite good results in general for skin colour detection, specially the Cr channel (90.19% of right detection) that saves the information for the red component of the colour model.

3.6 YPbPr Model

This colour space is the analog version of YCbCr model. So, this colour model also gets the best result for the channel Pr. We can conclude that it is equivalent to use YPbPr model and YCbCr model, but this last one is more used for skin detection than YPbPr.

3.7 YCgCr Model

This colour space is a variation of typical YCbCr model, since it uses Cg channel instead of using Cb channel (de Dios, 2004). In this colour space, using the three channels together, there is a great profit (from 89.8% of YCbCr to 92.63% of YCgCr) caused because green colour is quite better than blue colour to detect skin colour. In fact, the global right detections of this colour space are one of the highest in the study (only beaten by HSV colour space).

3.8 YDbDr Model

This colour model is quite similar to the previous ones, but it gives better results for blue channel than the other colour models (90.58% of right detections –the other colour spaces do not exceed 87.8% in any case–) without loosing precision in the other channels (specially in Dr channel, which is very important because Red is the channel that provides better results in skin detection). For this reason, YDbDr colour format provides quite good results studying the channels separately and also studying the three channels together (92.29% of hits).

3.9 HSV Model

This colour model provides the best results in our study. The right detection rate of this colour format using the three channels together is 95.06%. The best channel alone is S, which refers to saturation in the image, which provides an average of 94.04% of right detection rate. However, H component has a quite low success rate (only 72.16%) for the same reason that RGB had a quite low success rate for R channel: some skin parts of some faces in the database are confused with the background when the face has some brightness. Figure 3 shows an example of a picture of the facial database used in our study and the output provided by the K-Means classifier for each of the components of HSV colour space. Skin colour detections by the classifier are coloured in pink colour.

Figure 3: From left to right: original face, K-means classifier output for H channel, K-means classifier output for S channel and K-means classifier output for V channel.

3.10 CIE-XYZ Model

The results obtained with this colour space are quite similar to the obtained using RGB. However we can notice that XYZ provides better results for channel R (X in this case –87.44%–) than RGB format (82.79%). So, we can say that XYZ colour space is a bit more robust to illumination conditions than RGB.

4 CONCLUSIONS

We have done a complete study at pixel level of 10 different colour spaces using typical images in face recognition systems. The purpose of this study was to perform an objective comparison among the most used colour spaces in skin detection to discover which colour model provides the best results. We can group the different colour spaces into 4 different families: RGB family (RGB and CMY), YUV family (YUV, YIQ, YCbCr, YPbPr, YCgCr, YDbDr), HSV family and CIE family. According to the obtained results, the most appropriate family for skin detection is HSV (because HSV colour format is the winner in our study). However, there is a component in all colour models which, in general, provides constant and positive results. This component is Red component (the more significant channel for skin detection).

We can also state that luminance channel (in colour spaces where it is separated from chrominance. –Y in almost all channels and V in HSV–) is not a very important channel in skin colour detection. In fact, we can also say that colour spaces where luminance and chrominance are separated get better results (RGB, CMY and XYZ colour spaces have the lowest right detection rates of all models).

All in all, the 10 colour spaces that we have studied provide quite good results in skin colour detection. In general, all colour models have reduced false positives and false negatives rates (peaks values are explained by some unlucky highlights in the face of some people), and the right detection rates are at least over 86% in all colour spaces, so we can conclude that all the models can be used for skin colour detection with more or less success and precision (this explains why in the bibliography there are studies using such amount of different colour spaces).

To sum up, after doing the quantitative study described in this paper, we can conclude that HSV colour space is the model which gets the best results for skin colour detection. On the other hand, there are colour spaces that obtain quite poor results, such as CMY, CIE-XYZ, YIQ or even RGB. In any case, it is possible to use almost any colour space to find skin colour because with the appropriate classifier and some pre-processing in the images (such as giving higher values to contrast) most colour spaces have quite high right detections rates.

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