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Colour Feature Selection for Face Authentication

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Abstract

We address the problem of fusing colour information for face authentication. The performance of a face verification system in different colour spaces is experimentally studied first. The verification process is based on the normalised correlation measure within the LDA feature space. A sequential search approach which is in principle similar to the "plus L and take away R" algorithm is then applied in order to find an optimum subset of the colour spaces. Using the proposed method, the performance of the system is considerably improved as compared to the intensity space. The proposed colour fusion scheme also outperforms the best colour space in different conditions.

1 Introduction

Recently, in a number of studies, it has been demonstrated that colour information can improve the performance of the face recognition and verification systems. A brief history of different methods of involving colour features in the face verification systems can be found in [10] where a systematic evaluation of signal, feature and decision level fusion of data derived from a multispectral face image has been carried out. The authors focused on face verification using the Normalised Correlation and Gradient Direction metrics in Linear Discriminant Analysis (LDA) spaces associated with the respective R,G, B colour channels. The results demonstrated that the most beneficial fusion methods are the decision level and feature level fusion but the decision level fusion was computationally the simplest. In [6] the underlying physical process of image formation has been analysed and it has been shown that by adopting the intensity image, intensity normalised green and opponent colour channels we can separate the imaging effects of object shape and object albedo and create complementary image data channels that lead to face experts with an enhanced degree of diversity. It has been demonstrated that the fusion of these experts will result in significant improvements in performance over the system in which the face experts work with the raw R,G,B channel data or other colour spaces such as H, S, V.

However, the image formation process is very complicated and some of the simplifying assumptions are not valid in practice. Our experimental studies show that in different conditions different colour spaces can lead to better performance. Even in the same imaging conditions (lighting etc.), due to other factors such as the skin colour, the use of different colour spaces could be beneficial. The main idea behind the current study is to take into account as many as possible colour spaces for the verification process and then select the best colour space(s) depending on application. The colour space(s) are selected using a sequential search approach similar to the "Plus L and Take away R" algorithm. Surprisingly good results are obtained using the proposed method.

The paper is organised as follows. In the next section different colour spaces adopted in different machine vision applications are reviewed. The face verification process is briefly discussed in Section 3. The proposed method of colour space selection is described in Section 4. The experimental set up is detailed in Section 5. Section 6 presents the results of the experiments. Finally, in Section 7 the paper is drawn to conclusion.

2 Colour spaces

On computers, it is more common to describe colour as a mixture of three primary colours: Red, Green and Blue. However, it has been demonstrated that in different applications using different colour spaces could be beneficial. In this section some of the most important colour spaces are reviewed. Considering the R, G, B system as the primary colour space, we can classify the other colour spaces into two main categories: Linear and Nonlinear transformation of the R,G,B values.

2.1 Linear combination of R, G, B

CMY-based colour space is commonly used in colour printing systems. The name CMY refers to cyan, magenta and yellow. The RGB values can be converted to CMY values using:

$$C = 255 - R,\ \ M = 255 - G,\ \ Y = 255 - B \qquad (1)$$

There are several CIE-based colour spaces,but all are derived from the fundamental XYZ space:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.41 & 0.36 & 0.18 \\ 0.21 & 0.72 & 0.07 \\ 0.02 & 0.02 & 0.95 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (2)$$

A number of different colour spaces including YUV, YIQ, YES and YC_bC_r are based on separating luminance from chrominance (lightness from colour). These spaces are useful in compression and other image processing applications. A collection of the relevant equations can be found in [2]. $I1I2I3$ or Ohta's features [7] were first introduced for segmentation as optimised colour features and are shown in equations:

$$I1 = \frac{R+G+B}{3.0}, I2 = R - B, \quad I3 = 2G - R - B \quad (3)$$

LEF Colour Space defines a colour model that combines the additivity of the RGB model with the intuitiveness of the hue-saturation-luminance models by applying a linear transformation to the RGB cube [9].

2.2 Nonlinear combination of R, G, B

The chromaticities for the normalised RGB are obtained by normalising the RGB values with the intensity value:

$$r = R/I, \quad g = G/I, \quad b = B/I \quad (4)$$

where $I = (R + G + B)/3$. Similar equations are used for normalising the XYZ values. The result is a 2D space known as the CIE chromaticity diagram. The opponent chromaticity space is also defined as

$$rg = r - g, \quad yb = r + g - 2b \quad (5)$$

Kawato and Ohya [5] have used the ab space which is derived from NCC rg-chromaticities as:

$$a = r + g/2 \quad b = \sqrt{3}/(2g) \quad (6)$$

In [12], two colour spaces namely $P1$ and $P2$ have been defined by circulating the r, g and b values in equation 5. Log-opponent (or Log-opponent chromaticity) space has been applied to image indexing in [1]. The space is presented by equations:

$$\begin{aligned} Ln_{rg} &= \ln(R/G) = \ln R - \ln G \\ Lnyb &= ln(\frac{R.G}{B^2}) = \ln R + \ln G - 2\ln B \quad (7) \end{aligned}$$

TSL (Tint - Saturation - Lightness) colour space is also derived from NCC rg-chromaticities [11].

$l1l2l3$ colour space as presented in [4] has been adopted for colour-based object recognition. Many people find HS-spaces (HSV, HSB, HSI, HSL) intuitive for colour definition. For more information about the relevant equations used in this study, the reader is referred to [3].

3 Face verification process

The face verification process consists of three main stages: face image acquisition, feature extraction, and finally decision making. The first stage involves sensing and image preprocessing the result of which is a geometrically registered and photometrically normalised face image. The raw colour camera channel outputs, R, G and B are converted according to the desired image representation spaces. In this study different colour spaces reviewed in the previous section were considered.

In the second stage of the face verification process the face image data is projected into a feature space. The final stage of the face verification process involves matching and decision making. Basically the features extracted for a face image to be verified, $\mathbf{x}$, are compared with a stored template, that was acquired on enrolment, $\boldsymbol{\mu}_i$. In this study we adopted the Normalised Correlation (NC) measure in the Linear Discriminant Analysis (LDA) feature space for decision making [10]. The score, s, output by the matching process is then compared to a threshold in order to decide whether the claim is genuine or impostor. If this final stage of processing is applied to different colour spaces separately, we end up with a number of scores, $s_k = s(\mathbf{x}_k), \quad k = 1, 2, \ldots, N$ which then have to be fused to obtain the final decision. The adopted fusion method is studied in the next section.

4 Colour space selection

One of the most exciting research directions in the field of pattern recognition and computer vision is classifier fusion. Multiple expert fusion aims to make use of many different designs to improve the classification performance. The approach we adopted for selecting the best colour space(s) is similar in principal to the sequential feature selection methods in pattern recognition [8]. In this study, the Sequential Forward Selection (SFS), Sequential Backward Selection (SBS) and Plus'L' and Take away 'R' algorithms were examined for selecting an optimum subset of the colour spaces. Two simple fusion rules, the sum rule and the voting scheme were used in order to combine the scores of the selected colour based classifiers. The selection procedure keeps adding or taking away features (colour spaces in our case) until the best evaluation performance is achieved. The selected colour spaces are then used in the test stage.

5 Experimental design

The aim of the experiments is to show that by fusing the sensory data used by component experts, the performance of the multiple classifier system considerably improves. We use the XM2VTS database [1] and its associated experimental protocols for this purpose.

The XM2VTS database is a multi-modal database consisting of face images, video sequences and speech recordings taken of 295 subjects in 4 sessions at one month intervals. Eight images from 4 sessions are used. For the task of personal verification, a standard protocol for performance assessment has been defined. The so called Lausanne protocol splits randomly all subjects into client and impostor groups. The client group contains 200 subjects, the impostor group is divided into 25 evaluation impostors and 70 test impostors.

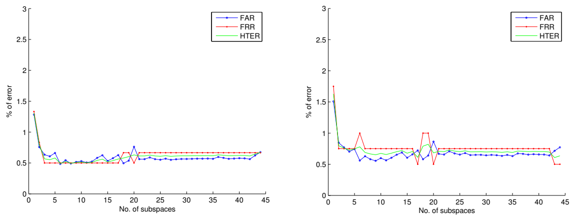
From these sets consisting of face images, training set, evaluation set and test set are built. There exist two configurations that differ by a selection of particular shots of people into the training, evaluation and test sets. The training set is used to construct client models. The evaluation set is selected to produce client and impostor access scores, which are used to find a threshold that determines

[1] http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/

if a person is accepted or not. In this study, the threshold have been determined based on the Equal Error Rate criterion, i.e. by the operating point where the false rejection rate (FRR) is equal to the false acceptance rate (FAR). False acceptance is the case where an impostor, claiming the identity of a client, is accepted. False rejection is the case where a client, claiming his true identity, is rejected. The evaluation set is also used in fusion experiments (classifier combination) for training. The sequential search algorithms pick the best colour spaces using this set of data.

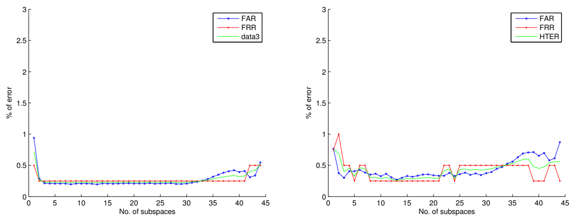
Finally the test set is selected to simulate realistic authentication tests where impostor's identity is unknown to the system. The performance measures of a verification system are the False Acceptance Rate and the False Rejection Rate.

The original resolution of the image data is 720×576. The experiments were performed with a relatively low resolution face images, namely 64×49. The results reported in this article have been obtained by applying a geometric face registration based on manually annotated eyes positions. Histogram equalisation was used to normalise the registered face photometrically.



(a) Evaluation (b) Test

Fig. 1. Plus 2 and Take away 1 results (configuration 1).



(a) Evaluation (b) Test

Fig. 2. Plus 2 and Take away 1 results (configuration 2).

6 Experimental results

Table 1 shows the performance of the face verification system for the individual colour spaces using the first configuration of the Lausanne protocol. The values in the table indicate the FAR and FRR in both evaluation and test stages. As we expect, the best performance is obtained neither in the original RGB spaces nor in the intensity space. Individually some other colour spaces such as U in the YUV space or opponent chromaticities can lead to better results. Table 2 shows some of the results of the same experiments for the second XM2VTS configuration.

In the next step, the adopted search method, Plus 'L' and Take away 'R' algorithm was used for selecting a subset of colour spaces. Figures 1 and 2 show the resulted error rates for different number of colour spaces in configurations 1 and 2 respectively. In the search algorithm $L = 2$ and $R = 1$. Before fusing, the scores associated to each colour space were appropriately normalised. The normalised scores were then combined using averaging. These plots show that by increasing the number of colour spaces intelligently, the TER first rapidly decreases. Then, for a larger number of colour features, the TER increases gradually or remains relatively constant. From these plots, one can also see that the behaviour of TER versus the number of colour features in the evaluation and test stages is almost consistent. Therefore, the optimum subset of colour features can be found in the evaluation step by looking for the point after which the performance of the system is not significantly improved by increasing the number of colour spaces.

Table 3 also contains a summary of the fusion results using the proposed algorithm. Note that using the search algorithm, colour spaces are selected from the evaluation data for the whole data set. However, for different conditions, different spaces are selected. In the case of the experimental protocols of the XM2VTS database, Lnrg, Q(YIQ),X(CIEXYZ) spaces have been selected for the first configuration while B(Japan), U(YUV), Yn, b, bg(opp-chroma), F(LEF), E(LEF) and I2(I1I2I3) have been adopted for the second one. Compared to the intensity space, the selected set of colour spaces after fusion yielded a total error rate on the test data which decreased from 3.49 and 3.29 to 1.55 and 0.52 for the first and second protocol configuration respectively. These results demonstrate that the proposed fusion method considerably improves the performance of the face verification system.

Table 3. ID verification results on XM2VTS configurations using the proposed colour fusion method.

	Evaluation			Test		
	FAR	FRR	TER	FAR	FRR	TER
Config. 1	0.48	0.5	0.98	0.55	1.0	1.55
Config. 2	0.19	0.25	0.44	0.27	0.25	0.52

7 Conclusions

We addressed the problem of fusing colour information for face authentication. In a face verification system which is based on the normalised correlation measure within the LDA face space, a sequential search approach similar to the "plus L, and take away R" algorithm was applied in order to find an optimum subset of the colour spaces. Using the proposed method, the performance of the verification system was considerably improved as compared to the intensity space. The proposed colour fusion scheme also consistently outperforms the best colour space in different conditions.

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Table 1. Results (per percent) using different colour spaces in the Evaluation and Test steps (configuration 1).

subspace	R	G	B	I	Hue	Sat	Value	r	g	b
FAR Eval.	1.94	1.91	2	2.18	2.1	1.72	2.05	1.8125	1.62	1.782
FRR Eval.	2.33	2.17	1.667	1.83	1.667	1.83	2.1667	2	1.33	1.667
FAR Test	2.13	1.92	2.24	2.24	2.027	1.78	2.34	1.96	1.62	1.817
FRR Test	2	1.75	1.5	1.25	0.5	1.25	2	0.75	1	1.25
subspace	Tint	S(TSL)	luma	V(YUV)	rg	U(YUV)	Cr	I2	I3	E(LEF)
FAR Eval.	1.425	1.28	2.04	2.38	1.32	2.25	1.56	2.16	1.577	2.235
FRR Eval.	1.67	1.33	2.33	2.33	1.67	1.67	2	2.33	1.83	2
FAR Test	1.258	1.51	2.062	2.36	1.467	2.08	1.94	2.12	1.59	2.36
FRR Test	1	1.75	1.5	0.75	1.25	0	1.5	0.75	0.75	0.5
subspace	F(LEF)	CIE(X)	CIE(Y)	CIE(Z)	Y(YES)	E(YES)	S(YES)	I(YIQ)	Q(YIQ)	a(ab)
FAR Eval.	1.49	2.39	2.35	2.08	2.03	2.16	1.95	2.13	1.81	1.76
FRR Eval.	1.67	1.83	1.83	1.83	2.33	1.83	2	2.17	1.833	1.833
FAR Test	1.37	2.51	2.43	2.34	2.04	2.033	1.79	2.4	1.7	1.87
FRR Test	0.5	1.25	1.5	1.75	1.5	0.75	0.25	1.5	0.75	1.5
subspace	b(ab)	Lnrg	Lnyb	l1	l2	l3	HSL(L)	Xn	Yn	Zn
FAR Eval.	1.58	1.3	1.69	2.41	2.19	1.71	2.13	1.79	1.6	1.65
FRR Eval.	1.5	1.67	1.5	1.833	2.5	1.67	2.33	1.83	1.5	1.667
FAR Test	1.628	1.4027	1.7973	2.09	2.25	1.58	2.23	1.892	1.65	1.6902
FRR Test	1	1.75	1.25	1	1.25	1.5	1	1	0.5	1.25
subspace	CMY(C)	CMY(M)	CMY(Y)	bg						
FAR Eval.	2.22	1.92	2.032	1.47						
FRR Eval.	2.5	2.17	1.67	1.67						
FAR Test	2.46	1.92	2.28	1.15						
FRR Test	2	1.75	1.5	0.75						

Table 2. Identity verification results using some of the colour spaces (configuration 2).

subspace	R	G	B	I	Hue	Sat	Value	r	g	b	U	Yn	bg	F(LEF)
FAR Eval.	1.19	1.40	1.295	1.225	1.26	1.03	1.003	1.51	0.75	1.00	0.87	0.89	0.82	0.87
FRR Eval.	1.5	1	1.25	1.25	1.25	1.25	1.25	1.25	0.75	1.25	1	1	1	1
FAR Test	1.57	1.82	1.93	1.79	1.15	1.46	1.31	2.16	0.77	1.80	1.06	1.12	1.03	1.24
FRR Test	1.5	1.25	1.5	1.5	0.5	1	1.75	1.25	0.5	0.75	1	0.5	0.75	1.25

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