An Effective Profile Based Video Browsing System for e-Learning

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Abstract: E-learning has acquired a prime place in many discussions recently. A number of research efforts around the world are trying to enhance education and training through improving e-learning facilities. This paper briefly explains one such attempt aimed at designing a system to support video clips in e-learning and explains how profiles of the presenters in video clips can be used to improve the usefulness of e-learning systems. The system proposed is capable of storing educational video clips with their semantics and retrieving required video clip segments efficiently on their semantics. The system creates profiles of presenters appearing in the video clips based on their facial features and uses these profiles to partition similar video clips into logical meaningful segments. The paper also discusses one of the main problems identified in profile construction and presents a novel algorithm to solve this problem.

Keywords: eigenfaces, eigenvectors, face recognition, image normalisation, principal component analysis, e-learning.

1. Introduction

E-learning is one of the fastest growing areas today. The main emphasis of e-learning is the management and delivery of quality teaching material electronically without the limitation of the learner access location and time. It includes the use of multimedia involving more than one form of media such as text, graphics, animation, audio, and video. Several approaches have been proposed to increase the acceptance and usage of existing e-learning platforms in education, but most of them are restricted in flexibility with regard to the content and adaptation to the user's skills (Lincoln et al (2001). Video Clips have been used widely in different application domains to deliver information efficiently and effectively. However, the large amount of visual information, carried by video documents requires efficient and effective indexing and searching tools to obtain their maximum benefit in an e-learning environment. The detection and recognition of faces in e-learning video clips where presenters explaining some phenomena, makes automatic indexing feasible to support assertions based on meaningful descriptions of content such as "presenter A and B talking about software engineering". In recent years many different approaches to video indexing have been developed (Lorente and Torres (1998). Most methods for video indexing use low-level features like texture or colour. The main drawback of low-level feature oriented video indexing is that they fail to recognise people and hence person-based indexing is not possible. People are one of the most important types of object in video sequences. Therefore indexing approaches used in e-learning systems have to be extended to cover the detection and recognition of people in video sequences.

The paper describes an architecture that we have implemented to support the integration of video clip into an e-learning system and efficient use of such video clips in e-learning. In our earlier publications we have described a multimodal multimedia database system that we have developed to support content-based indexing, archiving, retrieval and on-demand delivery of audiovisual content in an e-learning environment (Premaratne et al 2005, 2004). In this system, a feature selection and a feature extraction sub-system have been used to construct presenter profiles. The feature extraction process transforms the video key-frame data into a feature vectors in multidimensional feature space. This process can be considered as an implicit mechanism that both summarises and normalise the key-frame data. The effectiveness of a feature extraction procedure depends on the accuracy of feature selection process, which identifies effective and representative features of the objects involved. In this paper, we propose a novel profile normalisation algorithm to construct presenter profiles effectively. One of the distinct features of the algorithm is that it is capable of generating profiles at different illumination levels. Our method consequently solves the profile overlapping in eigenspace problem by using certain parameters. This work refines our earlier approach for profile construction, which averages all sample key-frame data to construct the presenter profiles. The remainder of this paper is

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organised as follows. The system architecture is briefly explained in Section two. Section three reviews a number of techniques related to our work. Section four explains our proposed algorithm for profile creation and profile normalisation. In sections five and six we give our evaluation and conclusion and finally in section seven we comment on future work possible based on this project and the experiences we have gained by using this system.

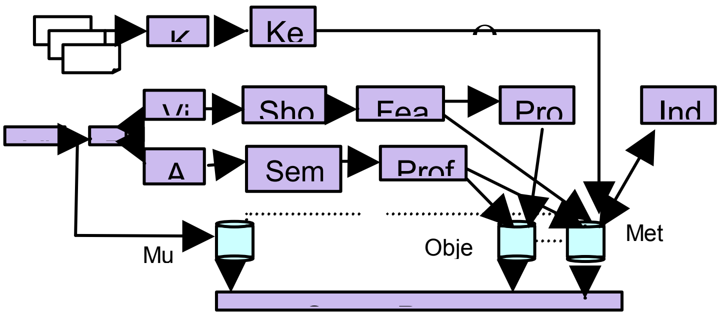


Figure 1: System architecture

2. System Architecture

The overall architecture of our system is shown in Figure 1. The main components of our architecture are: a Media Server, Meta-Data Database, Ontology and Object Profiles, Keyword Extractor, Keyword Organiser, Feature Extractor, Profile Creator and the Query Processor (Premaratne et al 2005, 2004). The functionality of each of these components are summarised in the following paragraph. The system stores all types of educational material varying from text documents to video clips in the media server. The keyword extractor extracts keywords from the main course materials and passes to the keyword organiser. The keyword organiser organises these keywords in ontology with links pointing to the respective documents to assist subsequent document browsing and retrieval. The feature extractor works on video clips and extracts audio and video features. These features are then used by the profile creator to construct profiles of presenters. Such profiles are subsequently used to create indices on the video clips. The query processor is the main user interface provided for the external users. It enables end users to browse and retrieve educational material stored in the media server easily and quickly by using the ontology and the indices managed by the system. The main emphasis of this paper is on the feature extraction and the profile creation and normalisation components of this system. The first step of the profile constructor is to extract features from the video Key-frames which containing most of the static information present in a shot. The main inputs to the profile constructor are these key-frames stored in the multimedia database (Figure 2).

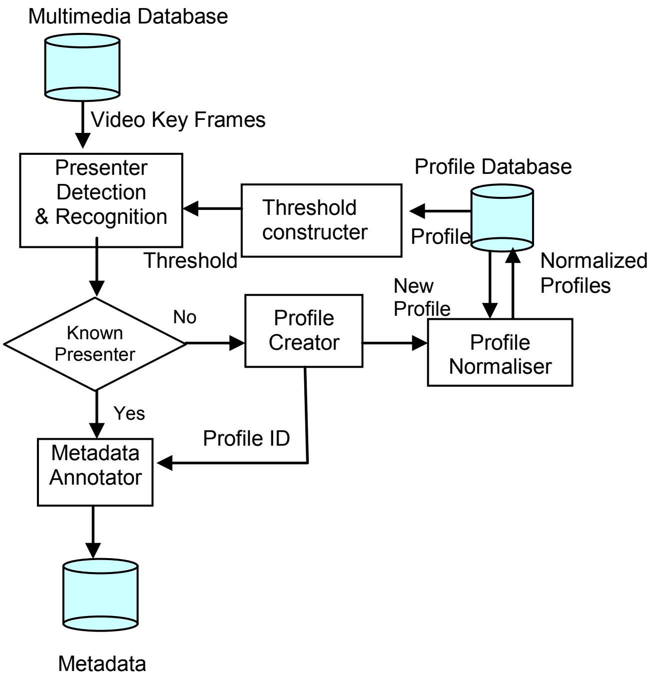


Figure 2: Profile construction and recognition process

The presenter detection and recognition process detects the faces in the key frame and try to match it with the presenter profiles available in the profile database. If the presenter in the key-frames matches with a profile then the system annotates the video shot with the presenter identification and maps it with the metadata database. On the other hand, if the current presenter's key-frames do not match with the available profiles then the profile creator will create a new presenter profile and insert it in to the profile database. In the following sub sections we have summarised the functionalities of profile construction, profile normalisation and threshold construction processes. In section 4, the profile construction algorithm is explained in details.

2.1 Profile construction

The profile construction is based on Principal Component Analysis (PCA) (Lorente and Torres 1998, Pentland et al 1994, Turk and Pentland (1991). The idea is to represent presenter's facial features in a featurespace where the individual features of a presenter are uncorrelated in the eigenspace. The feature space comprises of eigenvectors of the covariance matrix of the key-frame features. In this approach, PCA is computationally intensive when it is applied to the facespace. Through the experience we gained from our initial experiments we have realised that the efficiency of the PCA process in this context can be improved substantially by limiting the analysis to the largest eigenvectors of related key-frames instead of all eigenvectors of key-frames.

2.2 Profile normaliser

Profile normaliser acquires available profiles from profile database and executes the normalisation algorithm and returns the normalised profiles to the database. Since we get key-frames from different lighting conditions we have to have a proper dynamic profile normalisation algorithm to maintain the accuracy of the profile matching algorithm to an acceptable level. Therefore we concentrate on two descriptors, normally the mean intensity and its standard deviation of the data set that we use to construct presenter profiles. After investigating the variation of the illumination and the deviation of the mean intensity and standard deviation of a collection of profiles, we have identified few parameters that can be used to develop an algorithm based on these parameters to normalise the profiles with respect to illumination.

2.3 Threshold constructor

For recognition, we employee Euclidian distance algorithm to compute the distance between each profile in the database and the input face (Turk et al 1991). As the minimum distance classifier, it works well even when the key-frames have relatively small lighting and moderate expression variations. The weakness of this technique is that its performance deteriorates with the lighting variations in the key-frames. We have realised that this problem can be overcome by changing the threshold levels of the detection and recognition process by using parameters derived from key-frame intensity values. In our system the threshold constructor will calculate the light variation of each profile and adjust the threshold levels accordingly.

3. Related Work

In face recognition, a lot of problems are still open, particularly in uncontrolled environments, due to lighting, facial expressions, background changes and occlusion problems (glasses or hair for example) (Adini et al 1993, Phillips et al 2005). One of the main challenges in face recognition is to distinguish between intrapersonal variations (variations in appearance of the same person due to different expressions, lighting, etc.) and extra-personal variations (variations in appearance between persons). Among the few attempts aiming at identifying people in video sequences, Michael C. Lincoln and Adrian F. Clark of the University of Essex have proposed a scheme for independent face identification in video sequences (Lincoln and Clark 2001). The main drawback of this approach is that the recognition will only be comparable to the best front-face-only frames. Unlike this technique, eigenfaces relatively insensitive to small variation in scale, rotation and expression. A face recognition system based on Self Organising Maps (SOMs) and Convolutional Neural Networks (CNN) has been developed by Steve Lawrence. The problem with the SOM is that it arbitrarily divides input space into a set of classes of which the designer has no control or knowledge. Another problem with the neural networks is their inability to deal with the high dimensionality of the problem. For example to process an image of size 128 $\times$ 128 pixels requires a neural net with 16,384 input neurons. Furthermore, to train such a neural network, and ensure robust performance requires an extremely large training set (much bigger than 16,384). This is often not possible in real-world applications where only a limited number of images with different variations of an individual is available. The approach proposed by Turk and Pentland in 1991 is considered as one of the most successful systems for automatic recognition of human faces (Turk et al 1991). This approach is considered as a breakaway from contemporary research trend on face recognition techniques, which focused on detecting individual features such as eyes, nose, mouth, and head outline, and defining a face model based on position and size of these features, as well as geometrical relationship between them (Zhang et al 1997). The method uses the whole face region as the raw input to a recognition system, can be classified as an appearance based method.

4. Profile construction algorithm

In this section, we describe how we have improved the profile construction algorithm presented in Premaratne (2004, 2005)]. In our previous approach we have constructed presenter profiles by getting the average intensity values of the faces of presenters in the key-frames of the training set. From the results gathered we have realised that, our system performance deteriorates when the video key-frames are captured at different illumination conditions. The effects of illumination changes in key-frames are due to one of the two factors: The inherent amount of light reflected off the skin of the presenter, or the non-linear adjustment in internal camera control. Both of these conditions can have a major effect on facial features recognition. In our initial profile construction approach lighting variations result in producing similar profile for different presenter and hence overlap of profiles in the eigenspace (Figure 3).

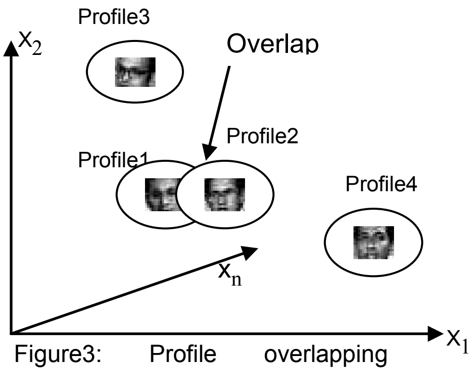


Figure3: Profile overlapping eigenspace

Figure 3 shows an example of profile overlapping in the n-dimensional eigenspace where axis X_1, X_2… X_n are the n-dimensions.

Even when there are only the illumination changes, its effects override the unique characteristics of individual features and thus greatly degrades the performance of state-of-the-art face recognition systems. We have come across a number of face image processing techniques as potential pre-processing step to improve the accuracy of the eigenface method of face recognition method (Broomhead and Kirby 2000, Chennubhotia et al and Dinggang ad Horace 1997). Also a number of attempts have been made to discover a relationship between mean, median and standard deviation of image intensities to construct a normalising algorithm to minimise the adverse effect of illumination on feature recognition (Broomhead and Kirby 2000). Motivated by Chennubhotla et al our research focused on finding out a suitable relationship between the mean and standard deviation of intensity values to improve recognition rate by separating out the overlapping profiles in the eigenspace. After conducting several experiments using these parameters we have discovered a strategy to reduce the effect of illumination by using the standard deviation (S) and the mean intensity ($\bar{X}$) of intensity values of key-frames. We have developed an algorithm to implement this strategy. The salient stage in the algorithm is the image intensity normalisation process, which is applied to all key-frames in the dataset, every time a new key-frame is added to the dataset.

$$\text{key-frame}_{i,j}\ (x,y) = (\ \text{key-frame}_{i,j}\ \bar{X}_{i,j} \quad -$$

key- $frame_{i,j}$ (x,y) = (x, y) pixel value of the j^{th} key-frame of i^{th} presenter

$\bar{X}_{i,j}$ = Mean intensity of j^{th} key-frame of i^{th} presenter

Equation 1 describes how our method transforms the key-frames of a presenter to the eigenspace. After experimenting with different parameters we have observed that the overlapping problem of eigenfaces can be controlled by introducing a parameter Γ to this image transformation. The parameter Γ is based on the standard deviation and the mean of intensity values of key-frames known to the system and computed as given in equation 2.

$$\Gamma = S + E_1 / S_{i,j} + \bar{X} + E_2 \quad \text{– (2)}$$

$\bar{X}$ = Mean intensity of all key-frames

S = Standard deviation of all key-frames

$S_{i,j}$ = Standard deviation of j^{th} key-frame of i^{th} presenter

The parameters E_1 and E_2 in the equation 2 are constants. To derive values for E_1 and E_2 we carried out experiments and analysed results on the recognition levels of the known presenters and unknown presenters. The sample set we used to determine these two constants included presenters with different illumination variations. One such result is shown below in figure 4. The values for S and $\bar{X}$ are 100.02 and 23.24 respectively. A complete result set is obtained by varying the values of ($S + E_1$) and ($\bar{X}$+ E_2). Only the best result is shown in figure 4. The recognition level can be described as the minimum value for a known face and the maximum value for an unknown face. The maximum recognition level 0.04 is obtained when $S + E_1$=140.02 and $\bar{X}$+ E_2=33.24. To obtain the exact values for the E_1 and E_2 we experimented with 20 presenters using five different datasets (Jonathon et al 2000). By evaluating this result set we achieved constants E_1 = 40 and E_2 = 10.

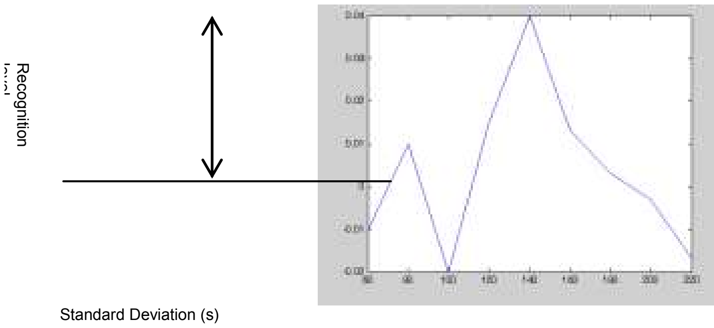


Figure 4: Determine the constants

After the key-frames are normalised by using the equation 1, we calculate the eigenvectors and eigenvalues of the normalised key-frames for each set of key-frames corresponding to a particular presenter. Once the eigenfaces have been computed, each face can be viewed in the eigenspace. Furthermore, good representations of the profiles can be obtained getting the largest eigenvectors available (Figure 4).

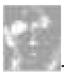
 =0.8731*  0.3736*  -0.7145*  ...

Figure 5: A profile developed in face space

In Figure 5, a presenter profile is developed into the facespace. Since a face captured from a video key-frame is 128*128 pixels, the dimensions of the corresponding eigenvalues generated will be 16384 * 1. We use 10 face frames from each presenter, therefore the dimensions of the covariance matrix is 16384 * 10. Consequently calculating this matrix would be very time consuming for the processor. This is one of the problems in using PCA in pattern. To overcome this problem, a computationally feasible method must be used to calculate eigenfaces. One such approach to reduce the dimensionality in face recognition is to sort the eigenvector according to their corresponding eigenvalues. The traditional motivation for selecting the eigenvectors with the largest eigenvalues is that it represents the amount of variance along a particular eigenvector (Turk et al 1991). By selecting the eigenvectors with the largest eigenvalues, one selects the dimensions along which the gallery key-frames vary the most. If we define e_i as the energy of the *i*th eigenvector, it is the ratio of the sum of all eigenvalues up to and including *i* over the sum of all the eigenvalues:

$$– (3) \qquad = \frac{\sum_{j=1}^{i} \lambda_j}{\sum_{j=1}^{k} \lambda_j}$$

Kirby (2000) defines e_i as the energy dimension. The variation depends upon the stretching dimension, also defined by Kirby. The stretch s_i for the ith eigenvector is the ratio of that eigenvalue over the largest eigenvalue (λ_1):

$$– (4) \qquad = \frac{\lambda_i}{\lambda_1}$$

Experiments were carried by selecting 120 key frames of 12 distinct presenters including 10 frames from each presenter. The calculated 120 eigenvector are show below in descending order.

(1.8787+ 1.494+ 0.952+ 0.778+ 0.446+ 0.367+ 0.307+ 0.287+ 0.223+ 0.215+ 0.200+ 0.179+ 0.167+ 0.155+ 0.133+ 0.121+ 0.116+ 0.098+ 0.095+ 0.087+ 0.076+ 0.074+ 0.074+ 0.070+ 0.066+ 0.061+ 0.060+ 0.057+ 0.054+ 0.051+ 0.049+ 0.048+ 0.047+ 0.046+ 0.045+ 0.043+ 0.042+ 0.041+ 0.039+ 0.038+ 0.036+ 0.035+ 0.035+ 0.034+ 0.033+ 0.032+ 0.031+ 0.030+ 0.030+ 0.029+ 0.029+ 0.028+ 0.027+ 0.026+ 0.026+ 0.025+ 0.025+ 0.024+ 0.023+ 0.023+ 0.022+ 0.022+ 0.022+ 0.022+ 0.021+ 0.021+ 0.020+ 0.019+ 0.019+ 0.019+ 0.018+ 0.018+ 0.018+ 0.017+ 0.016+ 0.016+ 0.016+ 0.016+ 0.016+ 0.015+ 0.015+ 0.015+ 0.014+ 0.014+ 0.014+ 0.013+ 0.013+ 0.013+ 0.012+ 0.012+ 0.012+ 0.012+ 0.012+ 0.011+ 0.011+ 0.011+ 0.011+ 0.011+ 0.010+ 0.010+ 0.009+ 0.009+ 0.009+ 0.009+ 0.009+ 0.008+ 0.008+ 0.008+ 0.007+ 0.007+ 0.005+ 0.005+ 0.003+ 0.003+ 0.0006+ 0.0003+ 0.00008+ 0.00006+ 0.00004+ 0.000001) X 10^9

$$\sum_{j=1}^{k} \lambda_j = 10.679781 \times 10^9$$

Using the equations (3) and (4), *s* and *e* are calculated for the sample set of 120 eigenvectors. A set of 60 key frames, which includes known presenters in the database, were selected to test the recognition performance and for each selected eigenvector set, recognition rate is calculated (See Table 1).

Table 1: The Energy and stretching dimensions.

Number of Eigen vectors	s	e	Correctly Classified frames	Recognition rate
5	0.2374	51.96%	11	21.67%
10	0.1144	65.05%	19	31.67%
15	0.07079	72.86%	23	38.33%
20	0.04631	77.70%	28	46.67%
25	0.03513	81.08%	34	56.67%
30	0.02715	83.73%	37	61.67%
35	0.02395	85.93%	40	66.67%
40	0.02023	87.83%	43	71.67%
45	0.01757	89.45%	45	75.00%
50	0.01544	90.72%	47	78.33%
55	0.01384	92.03%	49	81.67%
60	0.01224	93.18%	51	85.00%
65	0.01118	94.23%	53	88.33%

70	0.01011	95.18%	55	91.67%
75	0.00852	96.02%	55	91.67%
80	0.00798	96.78%	55	91.67%
85	0.00745	97.47%	55	91.67%
90	0.00639	97.97%	55	91.67%
95	0.00586	98.53%	55	91.67%
100	0.00532	99.04%	54	90.00%
105	0.00479	99.47%	54	90.00%
110	0.00373	99.84%	53	88.33%
115	0.00032	99.995%	52	86.67%
120	0.00000	100.00%	53	88.33%

Since the eigenvectors are ordered in high to low by the amount of variance found between key-frames along each eigenvector, the last eigenvectors are the smallest amounts of variance. The assumption can be made that noise is associated with the lower valued Eigenvalues where smaller amounts of variation are found among the key-frames Broomhead and Kirby (2000). This indicates that eliminating these Eigenvectors from the Eigenspace should improve the performance (Figure 6).

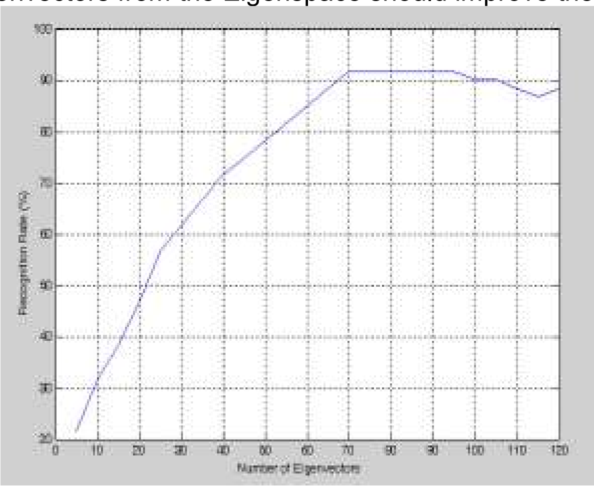


Figure 6: Performance when ordered by eigenvalue vs recognition rate.

By analysing the graph on figure 6 all Eigenvectors with s_i greater than a threshold can be retained. For the eigenvector selection process, threshold value (V_t) is determined to select the eigenvectors which is most suitable to construct a presenter profile (equation 5). Algorithm has been developed to calculate V_t by analysing the behaviour of each profile projection to the face space using different number of eigenvectors (figure 6).

$V_t = (V_{max}^{1/2}) * 3n$ - (5)

V_{max} = Maximum Eigenvalue

V_t = Threshold Value for Eigenvector Selection

Using the above algorithm we eliminate the eigenvectors less than V_t when constructing a presenter profile. For the data set on table 1,

$V_t = 1.5603830 \times 10^7$

Using our algorithm, the first 80 eigenvectors are selected and others are omitted. From the table 1 we have observed that when s is in between the limits of 0.01 and 0.006, the system acquires the highest recognition rate. Therefore the eigenvectors should be chosen between 70 and 90 for maximum accuracy.

5. Evaluation

Experiments were performed to evaluate our profile normalisation method using different data sets (Jonathon et al 2000). Frontal face key frames with lighting variations are selected from the database. A sample set of key-frames chosen for the evaluation are shown in figure 7 and the corresponding intensity histograms are shown in figure 8.

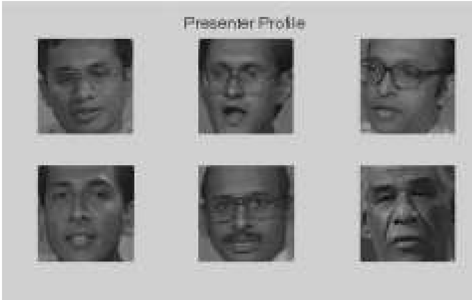


Figure 7: Presenter profiles

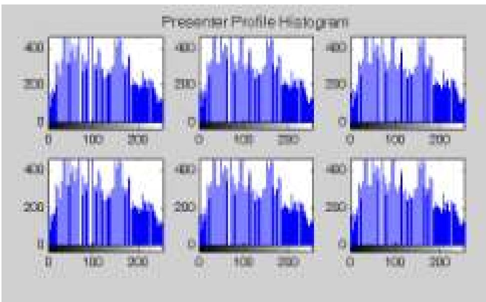


Figure 8: Colour histograms for presenter profiles

If the range of intensities of features in the key-frame can be determined beforehand, the key-frame contrast can be improved sufficiently while details are retained as much as possible. Although it is difficult to detect the intensity range of valid content in key-frame, the intensity range of face luminance variations can be computed by analysing peaks and valleys within the histogram. By analysing the above presenter profiles and histogram experimental results (figure 7 and 8) indicate that we cannot obtain good results under different illumination conditions using the conventional methods. In the presence of illumination, our system suffers errors which turn into the false identification of presenters. A sample set of Presenter profiles after applying the normalisation algorithm is shown in figure 9 and the corresponding intensity histogram of the normalised profiles are shown in figure 10.

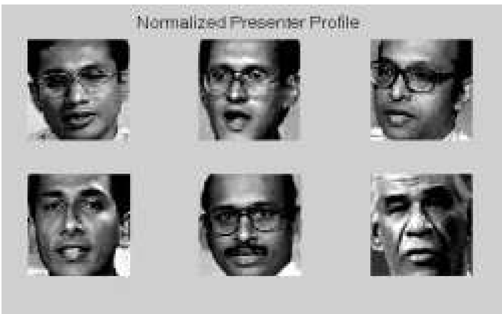


Figure 9: Presenter profiles

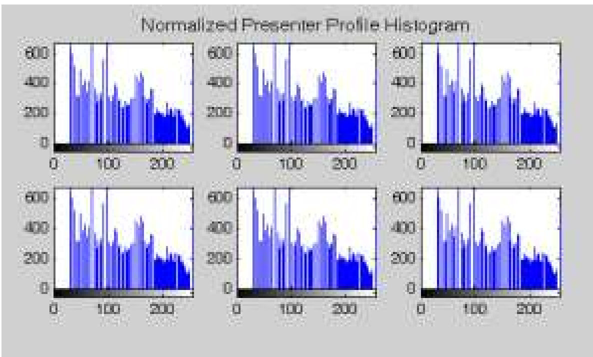


Figure 10: Colour histograms for normalised presenter profiles

Describing illumination conditions with a small number of parameters is quite difficult since the types or quantity of light sources have an infinite degree of freedom. Previous studies, however, have shown that illumination variations of an image can be described concisely, especially in the case of faces (Finlayson et al 1998). When comparing the intensity histograms (figure 8 and 10) we can investigate that the illumination factor in this experiment applies scaling factor to the luminance channel of the presenter, which affects the histogram and its variance. Each profile can be viewed as a set of features. When a presenter face is projected onto the facespace, its vector (made up of its weight values with respect to each eigenface) into the face space describes the importance of each of those features in the face. Figures 11 and 12 describe this process pictorially. In Figures 11 and 12, a face is developed into the facespace. The face is described in the face space by its eigenface coefficients (or weights). In Figures 11, The Face is developed using the original presenter's face and in figure 12 the face is developed after applying the normalising algorithm. Since the face developed in the face space is indeed a face, the weight of the first eigenface should be very high, almost equal to unity. (This useful property may be used to test key-frames for face–like qualities). The value of the weights decreases as the number of the eigenface increases. This is in conformity with the definition of eigenfaces. In fact, in figure 11 the weights are lower than the weights in figure 12. These experiments have proven that after normalising, the effectiveness of the profile projection has significantly improved.

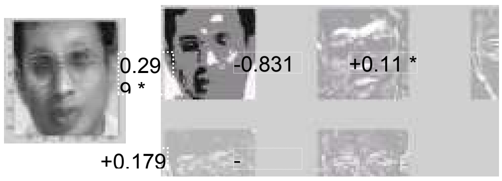


Figure 11: A profile developed without applying the normalising algorithm

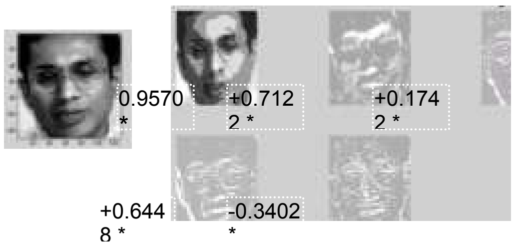


Figure 12: A profile developed after applying the normalising algorithm

Our experimental results show that the performance of the proposed method achieved a good success ratio (Figure 13 and 14). Furthermore, Verification tests are carried out to gather false acceptance rate (FAR) and false rejection rate (FRR) results from a data set comprised of key-frames that present typical difficulties when attempting recognition, such as strong variations in lighting direction and intensity (Figure 13). The total error rate is computed as a single measure of the effectiveness of the system and can be compute from FAR + FRR (Table 2).

Table 2: The summary of results

Number of Presenter Profiles	FAR %	FRR %	Total %
2	0	0	0
4	0	0	0
6	0	0	0
8	2	2	4
10	4	2	6
12	5	5	10
14	7	6	13
16	7	9	16
18	8	9	18
20	9	11	20

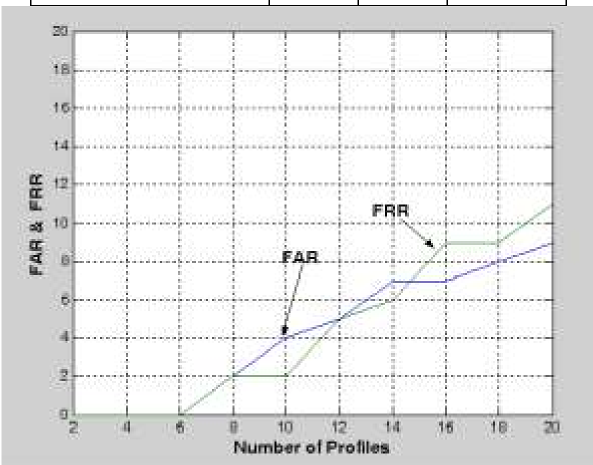


Figure 13: Eigenface error rate

Without any alterations to the eigenface technique itself, total error rate of 32.4% percent can be achieved (Premaratne et al 2004, 2005). By using our normalising algorithm the total error rate can be reduced to less than 20%. We tested the algorithm using two different counts of key frames of the same presenter to construct his profile. For the initial testing we have used 4 frames per presenter and for the second testing we have increased the key frames per presenter from 4 to 8. We were able to maintain an 80% recognition rate even when the profile database expanded to 20 (Figure 14). The recognition rate with the previous algorithm was 70%. Results indicate that our methodology is quite robust to both low resolution and luminance changes, which suggest that it can be used for face recognition even when with different lighting conditions.

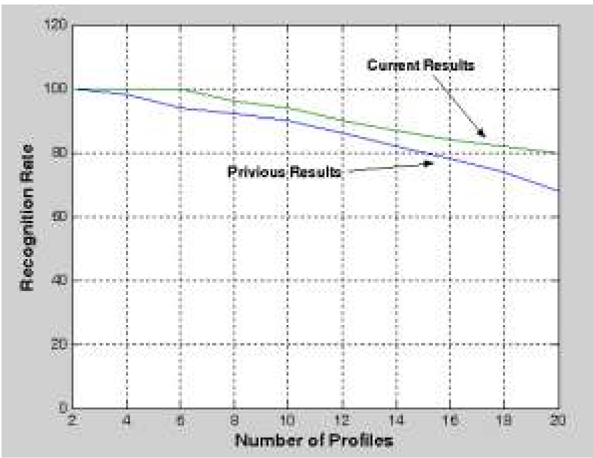


Figure 14: Recognition results

The experimental results show that the performance of the proposed method achieves a better success ratio (Figure 13 and 14). As shown in Figure 15, our algorithms can successfully rearrange profiles and overcome the profile overlapping.

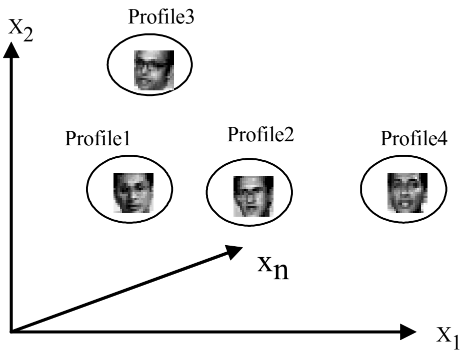


Figure 15: Normalised profiles

6. Conclusion

In this paper we have proposed a technique to deal with illumination variations in the eigenspace recognition framework. The proposed method was extensively evaluated on a database of 20 presenter profiles with varying illumination. Our experiment results show that the algorithm we have proposed can achieve a substantial improvement in face recognition. We have observed that effective normalisation of the video key-frames greatly increases the performance of the profile matching system. From the final results obtained it can be concluded that the new algorithm proposed in this paper works well under controlled environments and the recognition algorithm took advantage of the environmental constraints to obtain high recognition accuracy.

7. Future work

All current person recognition algorithms fail under the vastly varying conditions under which humans need to and are able to identify other people. Next generation person recognition systems will need to recognise people in real-time and in much less constrained situations. The work that had been done can be expanded in several directions and the algorithm can be improved to recognise more complicated video key-frames such as identifying presenters in different poses. Our system works well under small variations in orientation.

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