Invited Paper

Two Dimensional Statistical Linear Discriminant Analysis for Real-Time Robust Vehicle Type Recognition

I.Zafar, E.A.Edirisinghe, S.Acar, H.E.Bez
Department of Computer Sciences, Loughborough University, LE11 3TU, Loughborough U.K

ABSTRACT

Automatic vehicle Make and Model Recognition (MMR) systems provide useful performance enhancements to vehicle recognitions systems that are solely based on Automatic License Plate Recognition (ALPR) systems. Several car MMR systems have been proposed in literature. However these approaches are based on feature detection algorithms that can perform sub-optimally under adverse lighting and/or occlusion conditions. In this paper we propose a real time, appearance based, car MMR approach using Two Dimensional Linear Discriminant Analysis that is capable of addressing this limitation. We provide experimental results to analyse the proposed algorithm's robustness under varying illumination and occlusions conditions. We have shown that the best performance with the proposed 2D-LDA based car MMR approach is obtained when the eigenvectors of lower significance are ignored. For the given database of 200 car images of 25 different make-model classifications, a best accuracy of 91% was obtained with the 2D-LDA approach. We use a direct Principle Component Analysis (PCA) based approach as a benchmark to compare and contrast the performance of the proposed 2D-LDA approach to car MMR. We conclude that in general the 2D-LDA based algorithm supersedes the performance of the PCA based approach.

Keywords: Make and model recognition (MMR), Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), eigenvectors, 2D-LDA.

1. INTRODUCTION

A significant amount of research has been carried out in the area of computer vision based vehicle classification. However these classification techniques have been limited mostly to algorithms distinguishing between different categories of vehicles i.e. car, bus, truck etc. In contrast, an effective vehicle recognizing system solicits the need of correctly identifying the make and model of vehicles within a given category. Several effective vehicle recognition systems based on the number-plate exist. These have been successful in correctly recognising vehicle registration plates and have been therefore in widespread commercial use. However reports by police and media sources have indicated that number-plate cloning, i.e. using the bogus registration plates, have been recently used to breach the security provided by Automatic Number Plate Recognition (ANPR) techniques. This has been used to break security at automatic number plate identification based access control systems and avert congestion charging in busy city areas. This problem can be addressed and by enhancing the reliability of access control systems by using both ANPR techniques and a computer vision based automatic identification of a vehicle's visual description comprising of either one or more of properties such as, make, model, color etc. Vehicle Make and Model Recognition (MMR) provides the most effective functional enhancement to popular security and access control systems operated solely by number (license) plate recognition systems.

Vehicle MMR is a comparatively new research area. The basic idea is to extract suitable features from the images of a vehicle, which can help in recognizing its make and model. A relatively limited number of techniques that directly relate to vehicle MMR have been proposed in literature. Petrovic and Cootes [1, 2] proposed techniques for the recognition of cars, by extracting gradient features from images. A number of feature extraction algorithms including direct and statistical mapping methods were applied to regions-of-interest (ROIs) of frontal views of cars, to obtain sampled structures. These feature vectors were then extracted and classified using simple nearest neighbor classification methods. Daniel T.Munroe and Michael G.Madden [3] investigated the use of machine learning classification techniques in vehicle MMR. Initially a Canny edge detector followed by a dilation process was used to extract feature vectors. Subsequently different machine learning classifiers were used to determine vehicle make and model associated with each feature vector. L. Dlagnekov [4] in his paper explored the problem of MMR by using Scale Invariant Feature Transforms

Real-Time Image Processing 2007, edited by Nasser Kehtarnavaz, Matthias F. Carlsohn
Proc. of SPIE-IS&T Electronic Imaging, SPIE Vol. 6496, 649602, © 2007 SPIE-IS&T · 0277-786X/07/$18

[5]. It is used to identify the points of interest in car images which are subsequently utilized in matching. David Anthony [6] extended the work done by Dlagnekov by replacing the SIFT features with features which characterize contour lines. In this approach, initially, edges are extracted from the rear views of car images. These are then extended to line segments by using a strip based line generator algorithm and are subsequently used in matching.

All vehicle MMR approaches proposed in literature, summarized above, are based on an initial stage of feature detection, where these detected features are subsequently used in matching. For example, the majority of the methods are based upon using edge maps for feature extractions. However, edges are not reliable features as even the best edge extractor could fail to identify all edges that will be required in accurately defining the make and model of a vehicle. This is especially the case when the captured images of the vehicles are not clear, due to adverse lighting effects, occlusion and pose etc. The use of SIFT in MMR by Louka, promises to address some of these shortcomings of traditional feature based approached. Unfortunately it focuses on minute portions of image features, without considering any global features such as shapes or patterns, which are important in car MMR. Further it is computationally more costly as compared to the other traditional statistical approaches.

In order to resolve the above shortcomings and design a robust, real-time approach to vehicle MMR, in this paper, we propose the use of Two Dimensional Statistical Linear Discriminant Analysis (2D-LDA) [7]. Although appearance based methods such as Principle Component Analysis (PCA) and Linear Disciminant Analysis (LDA) have been successfully adopted in face recognition systems [8, 9, 11], their use in vehicle MMR provides additional challenges that needs careful investigation. These methods are based directly on pixel intensity values which provide global features. The use of PCA on detected feature vectors of images of vehicles has been previously proposed in literature [1,2]. However due to reasons discussed above, the accuracy of this approach is largely depended upon the accuracy of the feature detector used as a pre-processor. In this paper we propose and study the direct use of PCA as an appearance based car MMR system. We subsequently use it as a benchmark to prove the accuracy and robustness enhancements that are possible by replacing the use of PCA with LDA, in particular 2D-LDA.

For clarity of presentation this paper is divided into several sections. Further to the introduction provided to the problem domain of vehicle MMR in this section, i.e., section 1, section 2 presents the basic theory of LDA and described the practical use of 2D-LDA. It further provides suitable references to the theory of PCA, used in our experiments as a benchmarking approach. Section 3 presents the motivation behind the use of 2D-LDA in MMR as against competing technologies. Section 4 introduces proposed methodology and experimental design. Section 5 provides experimental results and an in-depth analysis. Section 6 finally concludes with an insight into the future directions of research.

1. THEORETICAL BACKGROUND

Among the appearance based recognition techniques, Principal Component Analysis (PCA) is one of the earliest techniques proposed for the identification and recognition of human faces [9]. Its purpose is to reduce the large dimensionality of the data space (observed variables) to the smaller dimensionality of feature space (independent variables), needed to describe the data economically. In the context to face recognition, using PCA, facial images are projected to a feature space which best describes the variation among known facial images. This feature space then enables efficient classification/recognition. We refer readers interested in the theory and applications of PCA to [9]. It is noted that in this paper we propose and use a PCA based car MMR technique as a benchmark algorithm for evaluating the proposed, novel, more robust and efficient approach to car MMR based on 2D-LDA.

Linear Discriminant Analysis (LDA) was first developed by R.A.Fisher [10] and was subsequently used by P.N.Belhumeour, et al. [11] to provide a basis for fisherfaces, now popularly used in face recognition. Belhumeour et. al. showed through experiments and in comparison with other popular pattern classification techniques namely, correlation and eigenface methods that fisherfaces provide a face recognition capability which is insensitive to large variations in lighting and facial expressions. In LDA, similar to in PCA, the image is initially linearly projected into a feature subspace. The projection method is based upon Fisher's Linear Dicriminant and produces well separated classes in a low-dimensional subspace. The basic idea of LDA is to maximize the ratio of between-class variance to the within-class variance in an image data set, thereby guaranteeing maximal separability. It also attempts to effectively draw a decision region between the given classes.

The between class scatter matrix, S_B, and the within class scatter matrix, S_w, defined in LDA theory [10] can be expressed as, $S_B = \sum_{i=1}^{c} N_i \left(\mu_i - \mu\right)\left(\mu_i - \mu\right)^T$ and $S_W = \sum_{i=1}^{c} \sum_{x_k \varepsilon X_i} \left(x_k - \mu_i\right)\left(x_k - \mu_i\right)^T$, where μ is the mean image of all training samples, μ_i is the mean image of class X_i, and N_i is the number of samples in class X_i.
If S_W is nonsingular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples, i.e, $W_{opt} = \arg\max_W \frac{|W^T S_B W|}{|W^T S_W W|} = [w_1 \, w_2 \ldots w_m]$, where $\{w_i \,|i = 1,2, \ldots m\}$ is the set of eigenvectors of $S_W^{-1} S_B$ corresponding to the m largest generalized eigenvalues $\{\lambda|i = 1,2, \ldots m\}$.

3. USE OF 2D-LDA IN CAR MMR - MOTIVATION

A PCA based car MMR approach has been previously proposed in literature [1], where a feature detector was used as a pre-processor. It was noted in section 1 that the negative effects on car MMR accuracy due to the functional limitations of feature detectors under adverse lighting and occlusion conditions can be removed by directly applying PCA on the images as an appearance based technique. Within our present research context we use this modified PCA based approach as a benchmark algorithm. Unfortunately, when used in a car MMR context, the general increase of the overall scatter between images solicited by PCA can result in miss-classification. It is noted that in the identification of vehicles (i.e. cars within our research context) the original data set can be separated into several groups, depending on make/model. Using PCA for recognition in such a scenario increases the within class scatter. Therefore two cars with the same make/model properties, but with slight illumination changes, can be scattered further apart and classified as being of different make/model.

On the other hand Linear Discriminant Analysis (LDA) [10] maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby maximizing separability. Unfortunately for a high dimensional and small sample size problem such as vehicle make and model recognition, the traditional LDA encounters two aspects of difficulties. Firstly, it cannot be used in cases where within-class scatter matrix is always singular. Secondly, the high dimensional image vectors lead to computational difficulty: LDA as proposed in [10] is based on analysis of vectors. Based on these vectors the covariance matrix is calculated and an optimal projection is obtained. However, typical images are high dimensional patterns and therefore results in a high-dimensional vector space, where the evaluation of the covariance matrix is computationally costly.

2D-LDA first proposed by Ming Li [7] provides effective solutions to the above problems of traditional one-dimensional LDA by directly extracting features from image matrix, rather than a feature vector created out of an image to compute the between-class scatter matrix and the within class matrix. This way evaluation of covariance matrix becomes easy. In the proposed work we have adopted 2D-LDA for robust and efficient car MMR. The readers interested in further details of 2D-LDA are referred to [7]. It is noted that neither the use of LDA nor the use of 2D-LDA in car MMR has previously been investigated in literature.

4. PROPOSED METHOD

Figure. 1 illustrates the block diagram of the proposed 2D-LDA based approach to car MMR. By replacing the 2D-LDA block by PCA, we obtain the PCA based car MMR approach we use as a benchmark to evaluate the 2D-LDA approach and its performance efficiency. In the proposed method we use a database of car data images where all of the images represent the frontal view of the cars. These images are taken under different lighting and weather conditions and from a roughly fixed distance and height. The operation of each block of Figure 1 can be briefly summarized as follows:

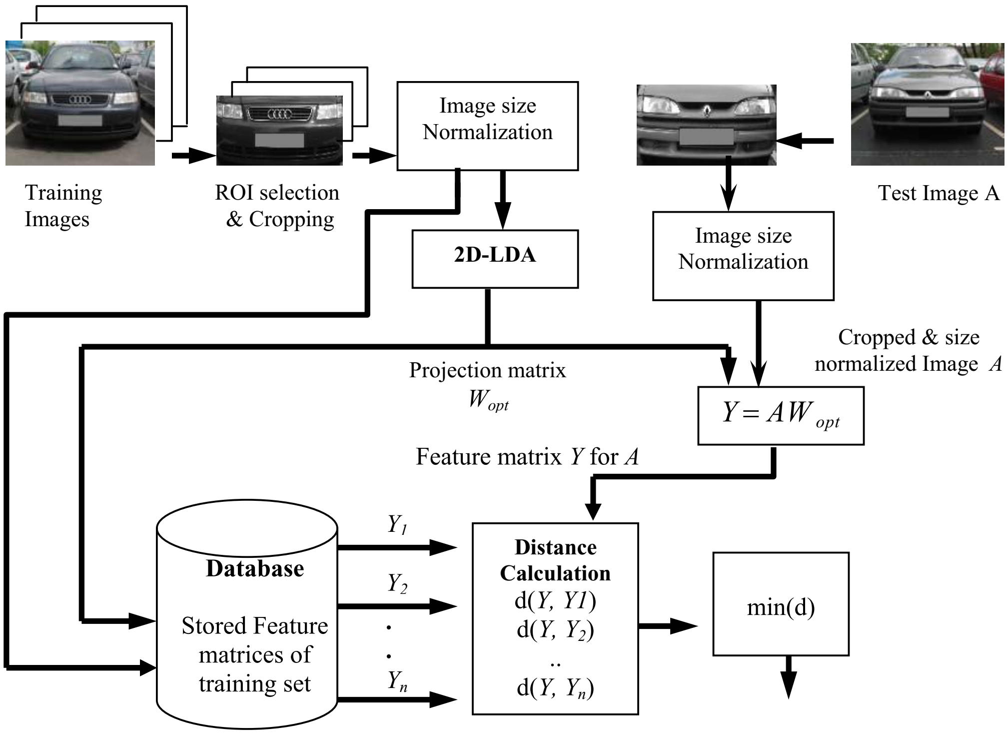


Figure 1. Proposed Car Make and Model Recognition System

4.1 Normalization

All images are initially cropped as illustrated in Figure 1 to extract the corresponding Regions-of-Interest (ROI) that contain visually significant features that can be used in distinguishing between different makes and models. For this purpose we have adopted the number plate detection and ROI measurement strategies proposed in [1,2]. As the resulting images are all of different sizes due to variation in image scale, a size normalization of these images is subsequently carried out with the use of the 'imresize' function of Matlab and using 'bilinear interpolation'.

4.2 Processing the training image set

The cropped and normalized images of the training image set are first grouped manually according to their make and model. Subsequently following 2D-LDA theory [7] summarised in section-2, the optimal projection matrix W_{opt} is obtained as follows:

- Assume that each training image is of dimensions $r \times c$. First of all the Fisher projection axes are constructed by finding the orthonormal eigenvectors of $S_W^{-1} S_B$ corresponding to first *m* largest eigenvalues. [Note: S_W and S_B are calculated as in section-2]. These eigenvectors corresponding to the largest eigenvalues (i.e. projection axes in the eigen-space) are used to obtain the optimal, Fisher projection matrix with dimensions $c \times m$, $W_{opt} = [w_1\ w_2 \ldots w_m]$.

The matrix W_{opt} is subsequently used for feature extraction. For a given image A, we have, $y_k = Aw_k, k = 1,2, \ldots, m \cdot$ These feature vectors are then placed in the form of a matrix $Y = [y_1, \ldots, y_m]$, the Fisher feature matrix of image A, with dimension $r \times m$.

4.3 Processing the test images

Each test image initially undergoes cropping and normalization as described above for the images in the training set. Using W_{opt} each normalized image is finally converted to a feature matrix in the eigen-space as described in section 4.2 above.

4.4 Classification

Classification of the test images into one of the given classes in the training set of car images is done by the using L_2 norm metric. We find the Euclidean distance between a test image feature matrix Y and each of the projections in the data base of training images as follows:

- Given two images A_1, A_2 represented by the Fisher feature matrices, $Y^1 = \left[y_1^1, \ldots, y_m^1 \right]$ and $Y^2 = \left[y_1^2, \ldots, y_m^2 \right]$, their overall Euclidean distance is defined as, $d\left(Y^1, Y^2\right) = \sum_{k=1}^{m} \| y_k^1 - y_k^2 \|_2$, where $\| y_k^1 - y_k^2 \|_2$ denotes the Euclidean distance between the two fisher feature vectors y_k^1 and y_k^2.

Finally, the car make and model of the training image which gives the minimum distance to the test image is selected as the make and model of the test image.

5. EXPERIMENTAL RESULTS AND ANALYSIS

We use a car image database of 200 images which comprises of 25 different car make-model groups (see Table 1). Each group has 8 images of different cars that belong to the same make-model classification. All images are grayscale and have been cropped to a resolution of 70×140 pixels, to include an area around the head lights, upper and bottom grills.

Table 1. 25 classes for various makes and models of cars

Classes				
Audi A4	Fiat Punto	Ford Ka	Renault Megane	Vauxhall Astra
Bmw3	Fiat Punto New	Ford Mondeo new	Renault Megane Coupe	Vauxhall Astra new
Bmw5 new	Ford Fiesta	Honda Civic new	Rover 25	Vauxhall Vectra
Citroen ax	Ford Fiesta new	Peugeot 306 new	Toyota Yaris	VolksWagen golf 3
Fiat Brava	Ford Focus	Renault 19	Toyota Corolla	VolksWagen Polo

To compare the performance of PCA and 2D-LDA approaches under normal lighting conditions 71 test images were used. Within this experiment, the average illumination levels of the test images used were not largely different from those in the training set. View occlusions were also not present. All eigenvectors were considered in creating the Eigen and Fisher feature matrices. Overall analysis revealed that the 2D-LDA based approach gave an identification accuracy of 87% as compared to the 78% accuracy obtained by the benchmark PCA based approach. The recognition accuracy was measured as a percentage of the ratio of the number of times the best matching make and model being the correct match, to the total number of images tested for a given experiment. Samples of experimental results are illustrated in Table 2.

To analyse the relative performance of the 2D-LDA and PCA approaches under varying illumination and occlusion conditions and to contrast with their performance under normal lighting and occlusion free conditions, a further experiment was carried out. A new set of 25 test images were constructed by altering a randomly selected sub set of test images used in the original test image set of 71. The alterations in the form of acute illumination changes and occlusion effects were introduced using Adobe Photoshop 7.0. The training image set used was not altered and was the same as in the previous experiment. Further all eigenvectors were considered in creating the Eigen and Fisher feature matrices. A sample of the results is illustrated in Table 3. Overall analysis revealed that the 2D-LDA based approach gave an identification accuracy of 76% as compared to the 48% accuracy obtained by the benchmark PCA based approach. It is observed that the 2D-LDA based approach is able to correctly identify the car make and model even under large occlusion differences. Occlusions of both white and black, were considered and the results were observed to be consistent for the 2D-LDA based approach. It was further observed that when using the PCA based approach under both large variations in illumination and occlusion the matching image found was mainly similar in the average illumination level, rather than in terms of features. This is justifiable as the theoretical evaluation of the PCA based approach suggests its appearance based, rather than the feature based matching pursuits.

Table 2. Comparison of 2D-LDA vs. PCA under normal lighting conditions. Only cases where results defer have been illustrated.

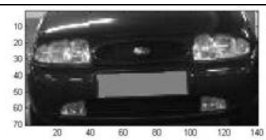
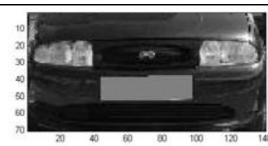
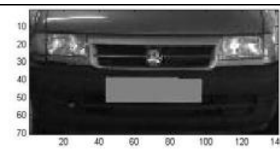
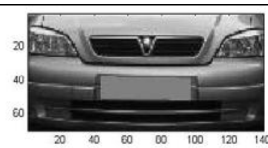
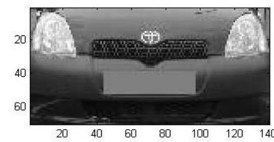
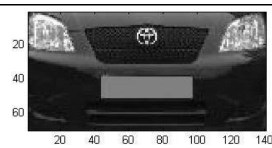
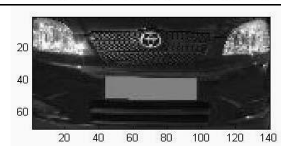
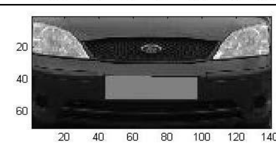
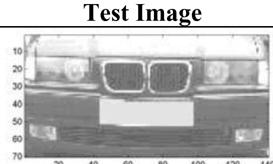
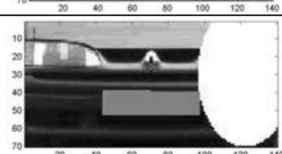
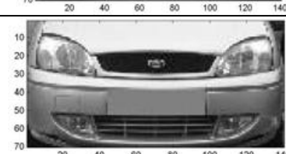
No	Test Image	2D-LDA Result	PCA Result
1			
2.			
3.			

Table 3. 2D-LDA vs. PCA under varying lighting and occlusion conditions. Only cases where results defer have been illustrated.

No	Test Image	2D-LDA Result	PCA Result
1			
2.			

The analysis of the above experimental results leads to the conclusion that the 2D-LDA based approach is more efficient and robust under varying illumination/lighting and occlusion conditions, when compared to the direct PCA based approach. Changing illumination and occlusion increases the variance amongst images. Unfortunately PCA further increases variance based on texture information, across all the images in the Eigen feature space, with disregard to any make-model groupings. This leads to potential misclassification. In contrast, in the Fisher feature space, despite increase in variance between images, 2D-LDA minimizes within class variance while maximising between class variance. However, despite the significantly better performance of the 2D-LDA based approach as compared to the PCA based approach, it is seen that both approaches have suffered a considerable loss of accuracy under the varying illumination and occlusion conditions.

To evaluate the performance of PCA and 2D-LDA approaches when using a reduced feature space, further experiments were carried out. The results are tabulated in Table 4. Experiments were carried out for both approaches, when all eigenvectors, all but the eigenvectors with the three largest eigenvalues (hereafter called the three most significant eigenvectors) and all but the eigenvectors with the hundred smallest eigenvalues (hereafter called the hundred least significant eigenvectors), were considered. Further two sets of experiments were performed. One with the initial training set of 200 images where the luminance variances of make-model groups were maintained within a limited range and an updated training set obtained by replacing some images within each group of the initial training set, with images that have higher luminance variances from the rest of the images in the group. In creating the above updated training set, the number of images per group, was maintained. A total of 71 images were used for testing.

Table 4. 2D-LDA vs. PCA in a reduced vector space

		MMR Accuracy (%)		
		Using All Eigenvectors	Dropped the three most significant	Dropping the 100 least significant
Initial training set	PCA	78	85	76
	2D-LDA	87	79	91
Updated training set	PCA	66	76	64
	2D-LDA	70	64	87

The Results in Table 4 illustrate that the performance of the PCA based approach degrades when the updated training set with images of higher illumination variation is used. This is expected as an increase of data scatter in the original image domain will lead to a largely increased scatter in their eigenspace domain, increasing chances of misclassification. Further the results in Table 4 illustrate that the accuracy of the PCA based approach increases when the three most significant eigenvectors are ignored. This is due to the fact that removing the most significant eigenvectors removes the consideration of illumination variances between cars of identical make-model in matching, thereby reducing chances of misclassification. This reasoning is further supported by the fact that dropping the most significant eigenvectors has resulted in a better percentage improvement of accuracy (i.e., 66% to 76% as against 78% to 85%), when the updated training dataset was used. Note that the updated training dataset contains groups of images that have high variations in luminance. Therefore using a PCA based approach that considers all eigenvectors is bound to perform sub-optimally. It is also seen that removing the hundred least significant eigenvectors, only marginally degrades the accuracy of the PCA based approach. However further removing low significance eigenvectors will reduce accuracy as the discrimination ability of the PCA is based on these eigenvectors.

The results in Table 4 also reveals that when using the 2D-LDA approach dropping the hundred least significant eigenvectors has resulted in a considerable improvement of recognition accuracy in contrast to the behaviour of the PCA based approach. It is further noted that the percentage improvement of accuracy obtained in the experiment where the updated training set is used (70% to 87%) is significantly more than where the initial training set is used (87% to 91%). These observations can be supported by the following theoretical reasoning: The least significant eigenvectors when using the 2D-LDA approach signifies instances of low, between class scatter to within class scatter ratio. The presence of cars that are identical in make-model but differ significantly otherwise due to the presence of illumination variations or occlusions, directly results in these eigenvectors. Ignoring these in matching therefore means ignoring the effects due to illumination variations and occlusions, which in turn positively impacts the recognition accuracy. The extra improvement observed above, when using the updated training set supports this argument. When the three most significant eigenvectors are dropped the 2D-LDA based approach behaves in contrast to the PCA based approach. The recognition accuracy is decreased. This can be supported by the fact that in the fisher feature space, the highly significant eigenvectors refer to instances where the ratio, between class scatter to within class scatter is high. Ignoring these eigenvectors can therefore directly lead to misclassification.

In summary it can be stated that in general the 2D-LDA based algorithm exceeds the performance of the PCA based approach. In particular the 2D-LDA outperforms the PCA based approach under varying illumination and occlusion conditions. The best performance with the PCA based approach is obtained when the more significant eigenvectors are dropped, whereas the best performance with the 2D-LDA is when the least significant eigenvectors are dropped.

It is further noted that once the training is completed, i.e. for example in the 2D-LDA approach, when the Fisher feature matrix is calculated using the database of training images, testing for the make-model of a new car can be performed real time.

6. CONCLUSION AND FUTURE WORK

In this paper we have proposed a novel, 2D-LDA based approach to car make and model recognition. We have compared the performance of the proposed method with a direct PCA based approach. Experiments were designed and carried out to compare and contrast the two approaches under normal illumination conditions, adverse illumination variations and in the presence of occlusions. The results conclude that in general the 2D-LDA performs better than the PCA in car MMR. In particular the 2D-LDA approach outperforms the PCA approach under varying illumination and occlusion conditions. Further detailed experiments have been provided to analyse the performance of the two algorithms when only a sub-set of eigenvectors are considered. We have shown that the best performance with the 2D-LDA approach is obtained when the eigenvectors of lower significance are ignored in contrast to the improvement obtained in the PCA approach when the eigenvectors with the highest significance are ignored. For the given database of 200 car images of 25 different make-model classifications, a best accuracy of 91% was obtained with the 2DLDA approach. The best accuracy obtained by the PCA approach was 85%.

We are currently in the process of investigating the performance of the 2D-LDA approach under varying pose and integrating the system within a multi-classifier system.

ACKNOWLEDGEMNT

The authors acknowledge the support of V.Petrovic [1] for providing a car image database for the experiments. This research was funded by the Innovative Manufacturing & Construction Research Centre, Loughborough University, UK.

REFERENCES

1. Petrović, V., Cootes, T, "Analysis of features for rigid structure vehicle type recognition", Proc. of the BMVC2004, 2004.
2. V.S. Petrovic and T.F. Cootes, "Vehicle type recognition with match refinement," International Conference on Pattern Recognition, vol. 3, pp. 95–98, August 2004.
3. Daniel T.Munroe, Michael G.Madden, "Multi-class and single-class classification approaches to vehicle Model recognition from images", Proc. AICS-05.
4. L. Dlagnekov. Video-based car surveillance: License plate make and model recognition. Masters Thesis, University of California at San Diego, 2005.
5. David G.lowe,"Distinctive Image Features from Scale-Invariant Keypoints", International Journal of Computer Vision, 2004.
6. David Anthony," More local structure information for Make -Model Recognition".
7. Ming Li, Baozong Yuan,"2D-LDA: A statistical linear discriminant analysis for image matrix", Pattern Recognition letters 26(2005), pp.527-532.
8. Aleix et al,'PCA versus LDA', IEEE transaction on pattern analysis and machine intelligence, vol 23, no.2,February 2001.
9. M.Turk and A.Pentland,"Eigenfaces for Recognition", CVPR'91, pp. 586-591, 1991.
10. R.A.Fisher,"The use of multiple measures in taxonomic problems,"Ann.Eugenics, vol.7, pp.179-188, 1936.
11. P.N.Belhumeour,et al.,"Eigenfaces vs. Fisherfaces: Recognition using class specific linear Projection", IEEE Trans.Pattern Analysis and Machine Intelligence, vol.19, no.7, pp.711-720, 1997.