Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection

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Summary: When it comes to face recognition paradigms, often times we are faced with adversities such as occlusion, illumination, expressions etc., therefore this paper focuses on identifying the best face recognition algorithm characterised by the error rate. The paper explores four different algorithms - Correlation, Eigenfaces, Linear subspace and Fisherfaces. Consequently all four techniques are tested experimentally with datasets under varying conditions and it was found that the best performance was attained by Fisherfaces which is invariant to large variations in lighting and expression.

Related work: The author closely follows the prior work regarding FLD and PCA in [4] [7][8][9].One case of face recognition using FLD was noted from [2] and pattern recognition from [1] [3] showed work analogous to the author's work on using Fisher's discriminator but for hand gestures. In testing the four approaches by the author, the datasets taken into consideration was from the Harvard and Yale database [6][5] through which the experimental results were able to be verified.

Approach: The problem is viewed as a pattern recognition paradigm transformation from high dimensional image space to a lower dimensional feature space. (i)**Correlation**: Uses the KNN algorithm with images in the learning set normalised which allows for high correlation with test images. Hence, there a degree of invariance towards light intensity. But, since this method involves comparing all image labels, this is computationally heavy and needs immense storage. In the learning set, if the lighting conditions diversely varies then the training set is not tightly clustered resulting in bad classification.

(ii)**EigenFaces**: To tackle computationally expensive tasks, PCA is used as a method of dimensionality reduction which identifies principal components which maximises the scatter of the samples projected into a lower n-dimensional subspace. The linear transformation is defined as $y_n = W^T x_k$. W_{opt} is chosen to maximise scatter matrix of the projected samples = $W_{opt} = argmax_W |W^T S_T W|$.But the within class scatter invariably increases and retains the variations due to lighting.

(iii)**Linear subspaces**: Based on the assumption that without any shadowing imahes follow Lambertian principles, a 3D basis containing 3 different lighting conditions for an image is constructed and recognition is achieved comparing the distance of the new image to the linear subspaces to find the one with the least distance. This method would be ideal if there is no shadowing and facial expressions, it is also computationally expensive due to each length computation and requires the storage of 3 image basis per image.

(iv)**FisherFaces**: This is a class specific method where the shape of the scatter is controlled through linear projections making it more reliable in classification. The main objective is to choose a $\boldsymbol{W}$ in order to maximise the between class to within class scatter ratio. $W_{opt} = argmax_W \frac{|W^T S_B W|}{|W^T S_W W|}$. The issue of singularity matrix is overcome by firstly reducing the dimensions using PCA and further using FLD. A new optimal solutions is $W_{opt} = W_{fld}^T W_{pca}^T$.

Experiments and Results: (i) Lighting - 5 subsets constructed based on change in lighting. Interpolation and extrapolation - Fisherface had the least error rate and all methods give good results for frontal illumination but in the case of varying illumination, Fisherfaces outperforms the rest and computationally cheap. (ii)Expression, eye wear and lighting: Imageset consisted of faces with expressions, facial hair and eye-wear. It follows the leaving-one-out strategy. It could be seen that the performance of Eigenfaces varied according to the components and yet it is evident that Fisherfaces had error rates less than half of the remaining showing true invariance to change in lighting, expression and occlusion.

Strengths: The author provides a clear and succinct approach to tackling adversities regarding face recognition due to change in lighting, and expression with detailed experimental backing. Fisherfaces utilize well the idea that the training set is labelled. The experiments are executed well to consider the most commonly occurring issues and Fisherfaces are found to be the most suitable approach even with respect to linear subspaces,Eigenfaces and correlation.

Weaknesses: Although this approach covers many issues, it still falls short on considering change in pose and also faces in a scene(natural scene), which pose a whole new set of problems. It most cases, using Fisher's method have shown that it is difficult to achieve optimum projection for separation in classes. Eigenfaces have additional constraints - need of having the number of face images greater than the dimension of the images but this causes issues in class overlapping which hampers with the recognition rate.

Reflections: The author does a good job in clearly comparing the necessary algorithms for robust face recognition when presented with change in illumination and expression, but it could be improved by considering a more wholesome dataset with characteristic problems. Since the assumption for this is based on the ideal Lambertain surface characteristics and also the linearity methods, these approaches will fail when there is non-linear and non-Lambertain representation of the images. Overall the paper presents a good approach to face recognition and provides a good platform to build on for future challenges to be addressed.

References

[1] S. Baker and S. K. Nayar. Pattern rejection. In *Proceedings CVPR IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 544–549. IEEE, 1996.

[2] Y.-Q. Cheng, K. Liu, J. Yang, Y.-M. Zhuang, and N.-C. Gu. Human face recognition method based on the statistical model of small sample size. In *Intelligent Robots and Computer Vision X: Algorithms and Techniques*, volume 1607, pages 85–95. International Society for Optics and Photonics, 1992.

[3] Y. Cui, D. L. Swets, and J. J. Weng. Learning-based hand sign recognition using shoslif-m. In *Proceedings of IEEE International Conference on Computer Vision*, pages 631–636. IEEE, 1995.

[4] R. O. Duda and P. E. Hart. Pattern recognition and scene analysis, 1973.

[5] P. Hallinan. *A deformable model for face recognition under arbitrary lighting conditions*. PhD thesis, PhD thesis, Harvard University, 1995.

[6] P. W. Hallinan et al. A low-dimensional representation of human faces for arbitrary lighting conditions. In *CVPR*, volume 94, pages 995–999, 1994.

[7] L. Sirovich and M. Kirby. Low-dimensional procedure for the characterization of human faces. *Josa a*, 4(3):519–524, 1987.

[8] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of cognitive neuroscience*, 3(1):71–86, 1991.

[9] M. Turk and A. Pentland. Face recognition using eigenfaces. In *Proceedings. 1991 IEEE computer society conference on computer vision and pattern recognition*, pages 586–587, 1991.