Eigenfaces vs Fisherfaces: Recognition Using Class Specific Linear Projection

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Summary: The paper proposes a face recognition algorithm insensitive to large light variations and facial expression based on the concept of Fisher's Linear Discriminant for linear projection of image into a lower dimensional subspace. The faces are assumed to be Lambertian surfaces and the non Lambertian regions with large deviation are discounted in the linear projections. The algorithm produces well separated classes and performs better than the Eigenface technique.

Related work: The paper builds further on the existing face recognition algorithms which work for little variation in lighting and facial expression. The Eigenfaces method [5, 6] and Correlation methods [1] can be considered to be the base work for the proposed algorithm. The algorithm adopts the concept of linear subspaces and Fisher's Linear Discriminant method to project to a lower dimension in a way which improves the class separability.

Approach: The Fisherfaces algorithm is compared against correlation, eigenfaces and linear subspaces algorithms for face recognition. Correlation [1] involves normalising images to have zero mean and unit variance which makes the results light independent when the classification is done using nearest neighbors. Eigenfaces algorithm [5, 6, 3] uses PCA for dimensionality reduction by linear projection of the images to maximise the scatter of all the samples. PCA tends to smear the classes together hence rendering linearly inseparable. Linear subspaces exploits the concept of Lambertian surfaces which suggests that the image intensity of any point is linear (in absence of shadowing) and hence an image can be reconstructed using linear combination of three original images insensitive to lighting [4]. Fisherfaces algorithm is based on Fisher's Linear Discriminant (FLD) algorithm [2] which makes linear projections such that the ratio of the between class variance and within class variance of the data is maximised. Between class variance is represented by: $S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T$ and within class variance is represented by $S_W = \sum_{i=1}^{c} \sum_{x_k \epsilon X_i} (x_k - \mu_i)(x_k - \mu_i)^T$ and the optimal projection $W_{opt} = argmax(\frac{\mod W^T S_B W}{\mod W^T S_W W})$, where c is the number of classes. In face recognition, S_W is singular and hence can be zero. Fisherfaces algorithm improves over this issue by projecting the image set to a lower dimension using PCA hence reducing the feature space to $N - c$ and then applies FLD. Now the optimal projection is represented by: $W_o^T{}_{pt} = W_f^T{}_{ld} W_p^T{}_{ca}$.

Experiments and results: Experiment was done on two data sets i) Harvard Lab data set which had symmetrically varying lighting: When the methods were trained on images with near frontal illumination and tested against varying light, Fisherface method and Linear Subspace methods have similar error rates which are significantly lower than Eigenface and correlation methods. ii) Yale dataset with variation in lighting and facial expression: Error rates were determined by leave one out strategy. Fisherface outperformed all the methods. Linear Subspace method did not perform well as the images were not in linear subspace due to varying expressions. Fisherface masks the points with high variability hence performing well even with varying expressions.

Strengths: Fisherfaces takes advantage of preservation of linear separability of the classes even with varying lighting to project the images to a lower dimension using FLD. FLD being a class specific method, simplifies the classification by achieving better in-between class scatter than PCA which tends to smear the classes together which are no longer linearly separable. The power of Fisherfaces to discount the highly variable points while face recognition benefits in classification with varying expressions as well unlike other algorithms.

Weaknesses: Fisherface algorithm currently throws away small number of principle components while dimension reduction which might result in loss of relevant information. The experiments for this paper were done on limited datasets and the performance of these algorithms on larger dataset should be done to see how well Fisherface performs then. Extreme lighting conditions are not considered for which new detection algorithms might be needed to support these methods.

Reflections: Even with varying lighting, in absence of shadowing an image can be considered to be a linear combination of images which makes the classification of images in varying lighting easier. Eigenfaces method can be used for face recognition in varying lighting but is not efficient for varying expressions. Fisherfaces method is better at handling the variation in lighting as well as expression simultaneously. More analysis should be done to get the performance of Fisherfaces on a larger database and shadowing in picture.

References

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