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Two Stage Nonparametric Discriminant Analysis for Small Sample Size Problem in Face Recognition

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Face recognition is one of pattern recognition problems which suffer from *Small Sample Size* (SSS). Non-parametric Discriminant Analysis (NDA) is a feature extraction technique in which between-class scatter $\mathbf{S}_b$ is defined non-parametrically and is generally of full rank thereby improving the SSS properties. On the other hand, dimensionality reduction is another paradigm widely applied to reduce redundancy and extract relevant information. In this paper, we propose *Two Stage NDA (TSNDA)* method which hybridizes the above two paradigms and effectively addresses SSS problem in face recognition. In the first stage, Principal Component Analysis (PCA) is applied to reduce redundancy while in second stage, NDA is applied for feature extraction. Experimental results on three publicly available datasets *viz.*, AR, CMU-PIE and YALE demonstrate the efficacy of the proposed method. In addition, the training time required by TSNDA is radically less in comparison to NDA rendering it suitable for real time applications.

Keywords : Discriminant, Hybrid, Illumination, Two Stage.

1. INTRODUCTION

Face recognition [1] is an important research area which has emerged in the past few decades. It has attracted the research community from diverse fields due to its increasing applications such as surveillance, forensic investigation, biometrics, ATM, access control, surveillance *etc.* [2]. In controlled environment such as frontal pose and proper illumination; face recognition can be performed to satisfactory levels. But in uncontrolled environment such as illumination changes, pose variation, expression variation, occlusion *etc.* [1,3] , the performance degraded considerably. Illumination variation is one such problem in which the intensity values of the facial image of a person gets modified. Adini *et al.*, [4] have pointed out that the identity of same person may be misclassified because of varying illumination. A survey of the illumination invariant face recognition methods is given by Zou *et al.*, [5]. One of these approaches is appearance based methods [6,7] in which the face image $(m \times w)$ of a person is represented as a vector in n-dimensional space such that $n = m \times w$. However, large value of n causes huge computational and storage requirements and it becomes difficult to work in such spaces. According to the criterion stated by Bellman [8], the sample size required to approximate a function of several variables grows exponentially with increase in the number of variables. This problem is well known in literature as curse-of-dimensionality or Small-Sample-Size (SSS) problem. Face recognition is a pattern recognition application which is confronted with SSS problem. Several techniques are proposed by various researchers to solve this problem.

One common approach to reduce the negative effects of SSS is to employ dimensionality reduction techniques. Many surveys of dimensionality reduction techniques are conducted from time to time by various researchers such as Carreira-Perpinan [9], Ambra *et al.*, [10] and

Table 4
Training Time Complexity of TSNDA algorithm

Computation Term	**Complexity**
Stage 1: PCA	
Total class scatter ($\mathbf{S}_t$)	Nn^2
Eigen-Decomposition of $\mathbf{S}_t$	$O(n^3)$
Let p is the number of dimensions retained such that p<< n	
Stage 2: NDA with reduced dimensionality p	
Within-class scatter ($\mathbf{S}_w$)	Np^2
Eigen-decomposition of $\mathbf{S}_w$	$O(p^3)$
Whitening of Data (If K_{wp} eigenvectors retained)	$K_{wp}^2 N + K_{wp} N$
$\mathbf{S_b}$ (non-parametric) on whitened data	$\frac{N(N+1)}{2} K_{wp}$
Eigen-Decomposition of $\mathbf{S}_b$	$O(K_{wp}^3)$
Transformation Matrix ($\mathbf{W}$) (If K_{bp} eigenvectors retained)	$K_{wp}^2 n + K_{bp} K_{wp} n$
Transformed Training data	$K_{bp} N n$

ties. Thus, NDA is less affected by SSS problem and also diminishes the effects of outliers if any. Dimensionality reduction is another paradigm widely applied to extract relevant information and reduce redundancy. In this paper, we proposed TSNDA which combines these two paradigms and effectively addresses the SSS problem in face recognition. In the first stage, PCA is applied to remove redundancy present in data samples while in the second stage, NDA is applied for feature extraction. The effectiveness of the proposed approach for reducing SSS effects is demonstrated by the experimental results on three publicly available datasets *viz.*, AR, PIE and YALE. Further, the time required by the proposed method is drastically less in comparison to original NDA method which further makes it suitable for real time face recognition. The proposed method works well in handling illumination variation problem in face recognition. In the future, we would like to propose feature extraction methods which are robust against SSS in conjunction with other challenges such as occlusion and facial expression.

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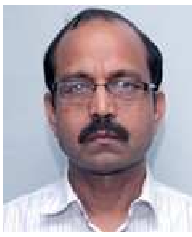

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