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Chapter V

Statistical Uncorrelation Analysis

ABSTRACT

This chapter shows a special LDA approach called optimal discrimination vectors (ODV), which requires that every discrimination vector satisfy the Fisher criterion. After introduction, we first give some basic definitions. Then, uncorrelated optimal discrimination vectors (UODV) are proposed. Next, we introduce an improved UODV approach, and offer some experiments and analysis. Finally, we summarize some useful conclusions.

INTRODUCTION

ODV is a special LDA approach that requires that every discrimination vector satisfy the Fisher criterion. Various literature discuss ODV. Foley and Sammon present a set of optimal discrimination vectors for two-class problems, which requires the discrimination vectors to satisfy the orthogonality constraint (Foley & Sammon, 1975). Foley's approach is called the Foley-Sammon ODV (FSODV). Okada and Tomita propose an optimal orthonormal system for discrimination analysis (Okada & Tomita, 1985).

Duchene et al. propose orthogonal discrimination analysis in a transformed space (Duchene & Leclercq, 1988). Liu, Cheng and Yang propose more comprehensive solutions for the ODV set (Liu, Cheng, & Yang, 1993).

While all of the above ODV approaches employ the orthogonality constraint, Jin, Yang, Hu, Tang and Lou recently proposed an UODV (Jin, Yang, Hu, & Lou, 1993) approach and a related theorem (Jin, Yang, Tang, & Hu, 2001). UODV uses the constraint of statistical uncorrelation. The experimental results show that UODV produces better outcomes than FSODV on the same hand-written data, where the only difference lies in their respective constraints. On the other hand, Yang, Yang, and Zhang (2002) prove that the uncorrelation constraint is theoretically superior to the orthogonality constraint. However, some disadvantages still exist in Jin's approach. First, in order to guarantee that S_w is nonsingular, it uses the between-class correlation matrix, $\sum_b = \sum_{i=1}^{c} m_i m_i^T$, as the production matrix of the KL transform, where m_i is the average value of the ith class samples. It is not a TPCA method that uses S_t as the production matrix. Therefore, it cannot reflect the total scatter of the whole sample set. Second, its theorem is merely suitable for a specific situation, where the non-zero discrimination values of the Fisher criterion are unequal mutually, implying that it cannot be applicable to other situations.

BASIC DEFINITION

Suppose that X is an N-dimensional sample set, and $w_1, w_2, \ldots w_c$ are C known pattern classes of X. Let m_i and $P_i (i = 1, 2, \ldots, C)$ be the mean vector and a priori probability of class w_i. Let m be the mean vector of X. The between-class scatter matrix, S_b, the within-class scatter matrix, S_w and the total scatter matrix, S_t, are defined as Equations 3.43, 3.37 and 3.41.

The Fisher criterion is expressed by the maximum value of the following function as Equation 3.31. And here, we change the symbol **w** to φ to explain the following problems simply.

The first step is to perform TPCA; that is, to take S_t as the production matrix of the K-L transform. Suppose that the rank of S_t is r_t. We get r_t eigenvectors corresponding to the non-zero eigenvalues of S_t, which form the transform matrix W_{TPCA}. Thus, any N-dimensional sample from X can be transformed into an r_t-dimensional vector. The reason we choose TPCA transform is TPCA has a favorable property; namely, the statistical uncorrelation. Suppose that there are two different discrimination vectors φ_1 and φ_2 ($\varphi_1 \neq \varphi_2$) The statistical uncorrelation in Jin, Yang, Hu and Lou (2001) is defined as:

$$\varphi_1^T S_t \varphi_2 = 0 \tag{5.1}$$

Let $W_{TPCA} = [w_1 \; w_2 \; \ldots w_n]$. According to the definition of W_{TPCA}, it is obvious that:

$$w_j^T S_t w_i = 0\,, \quad j \neq i\,, \quad 1 \leq (i, j) \leq n \tag{5.2}$$

Obviously, TPCA can satisfy the statistical uncorrelation.

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