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Chapter XIII

Feature Fusion Using Complex Discriminator

ABSTRACT

This chapter describes feature fusion techniques using complex discriminator. After the introduction, we first introduce serial and parallel feature fusion strategies. Then, the complex linear projection analysis methods, complex PCA and complex LDA, are developed. Next, some feature preprocessing techniques are given. The symmetry property of parallel feature fusion is analyzed and revealed. Then, the proposed methods are applied to biometric applications, related experiments are performed and the detailed comparison analysis is exhibited. Finally, a summary is given.

INTRODUCTION

In recent years, data fusion has been developed rapidly and applied widely in many areas, such as object tracking and recognition (Chiang, Moses, & Potter, 2001; Peli, Young, Knox, et al., 1999), pattern analysis and classification (Doi, Shintani, Hayashi, et al., 1995; Gunatilaka & Baertlein, 2001; Young & Fu, 1986), image processing and understanding (Ulug & McCullough, 1999; Chang & Park, 2001), and so forth. In this chapter, we pay most attention to the data fusion techniques used for pattern classification problems.

In practical classification applications, if the number of classes and multiple feature sets of pattern samples are given, how to achieve a desirable recognition performance based on these sets of features is a very interesting problem. Generally speaking, there exist three popular schemes. In the first one, the information derived from multiple feature sets is assimilated and integrated into a final decision directly. This technique is generally referred to as *centralized data fusion* (Peli, Young, Knox, et al., 1999) or *information fusion* (Dassigi, Mann, & Protopoescu, 2001) and is widely adopted in many pattern recognition systems (Li, Deklerck, Cuyper, et al., 1995). In the second, the individual decisions are made first based on different feature sets, and then they are reconciled or combined into a global decision. The technique is generally known as *distributed data fusion* or *decision fusion* (Peli, Young, Knox, et al., 1999). In the third scheme, the given multiple feature sets are used to produce new fused feature sets, which are more helpful to the final classification (Ulug & McCullough, 1999). The technique is usually termed *feature fusion*.

As a matter of fact, feature fusion and decision fusion are two levels of data fusion. In some cases, they are involved in the same application system (Gunatilaka & Baertlein, 2001; Jimenez, 1999). But, in recent years, decision level fusion, represented by multi-classifier or multi-expert combination strategies, has been of major concern (Huang & Suen, 1995; Constantinidis, Fairhurst, & Rahman, 2001). In contrast, feature level fusion has probably not received the amount of attention it deserves. However, feature level fusion plays a very important role in the process of data fusion. The advantage of feature level fusion lies in two aspects: First, it can derive the most discriminatory information from original multiple feature sets involved in fusion; Second, it enables eliminating redundant information resulting from the correlation between distinct feature sets and making the subsequent decision in real time possible. In a word, feature fusion is capable of deriving and gaining the most effective and least-dimensional feature vector sets that benefit the final decision.

In general, the existing feature fusion techniques for pattern classification can be subdivided into two basic categories. One is feature selection-based, and the other is feature extraction-based. In the former, all feature sets are first grouped together and then a suitable method is used to select most discriminative features from them. Zhang presented a fused method based on dynamic programming (Zhang, 1998); Battiti gave a method using supervised neural network; and recently, Battiti (1994), Shi and Zhang provided a method based on support vector machines (SVM) (Shi & Zhang, 1996). In the latter, the multiple feature sets are combined into one set of feature vectors that are input into a feature extractor for fusion (Liu & Wechsler, 2000). The classical feature combination method is to group two sets of feature vectors into one union-vector (or super-vector). Recently, a new feature combination strategy; that is, combining two sets of feature vectors into one complex vector, was developed (Yang & Yang, 2002; Yang, Yang, Zhang, & Lu, 2003; Yang, Yang, & Frangi, 2003). The feature fusion method based on union-vector is referred to as *serial feature fusion,* and that based on complex vector is called *parallel feature fusion*.

In this chapter, our focus is on feature level fusion. The distinction of *feature combination* and *feature fusion* is specified, and the notions of *serial feature fusion* and *parallel feature fusion* are given. The basic idea of parallel feature fusion is: The given two sets of original feature vectors are first used to form a complex feature vector space, and then traditional linear projection methods, such as PCA (see Chapter II) and LDA (see Chapter III) are generalized for feature extraction in such a space. The proposed parallel feature fusion techniques are applied to face recognition. The experimental

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