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Feature structure fusion and its application

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ABSTRACT

The structure of data is important to the recognition of data. It is a fundamental question how measures and complements the structure of multi-features, because the fusion structure of multi-features is more complete than that of the single feature. To settle the question, we propose three methods for feature structure fusion in feature vectors or feature vector spaces. Firstly, the applicability of the different metric is analyzed. Secondly, optimization questions of various features are constructed based on manifold learning methods. Finally, multiple target optimization questions are transformed to a single target optimization question, and the principle of feature structure fusion is uncovered. In the classification of shape analysis and human action recognition, it is proven that structure fusion methods are effective.

1. Introduction

With feature extraction methods and devices increasing, the different description of the same object may produce many features. The aim of feature fusion makes use of the complementary information of each feature get the complete structure of the object. Various features can describe the different characteristic of the same object, and the structure fusion feature can mine the intrinsic structure of the object from the diverse observation angles. It is shown that the intrinsic structure plays a key role for the effective detection and the reliable recognition [1–4]. In this paper, the intrinsic structure is defined by the interrelations of multiple features. It is a fundamental question what to do for obtaining the respective structure of the feature, and what to do for fusing feature structure for object classification. Therefore, we propose feature structure fusion methods, which can measure the structure through the different metric, and can construct a structure fusion feature through manifold learning methods to obtain the discrimination fusion feature. In previous research, we have gotten the preliminary result about structure fusion in literature [5]. This paper is the further research of structure fusion. The different points show two points. One is the relation of structure can be solved by optimization in this paper, and this relation is equal in each other in literature [5]. Other is structure fusion is deduced in other manifold learning methods for vector or vector space feature, and their application is extended in shape analysis and human action recognition in this paper.

The novelties of the paper have three points.

a. The applicability of three metric methods is analyzed. According to the above analysis, the different feature may select the various metric.
b. By solving multi-target optimization question, the principle of the structure fusion is explained, and then three methods are proposed for fusing the vectors features or the vectors space features.
c. The proposed methods are used for shape analysis and human action recognition. It is shown that the performance of the proposed methods is better than state of the art methods for classification.

There are many feature fusion methods based on machine learning in the recent research. According to learning types, these methods are divided into unsupervised learning methods and supervised learning methods. There are some representatively unsupervised learning methods as following. A straightforward feature fusion approach is to concatenate various features to a single feature [6]. Although it achieves a certain performance, the method meets the problem of "curse of dimensionality" and the repeated information. Feature fusion based on locally linear embedding [7] not only processes the fusion of the multi-feature but also reduces the dimension of the feature. Moreover, its performance is approximate to the performance of the feature fusion based on kernel method [8], which needs to select the kernel function and parameters. However, two methods ignore to measure the original structure, which is the interrelation of features. Locality-preserving canonical correlation analysis [9] obtains the fusion feature by

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maximizing the correlation of the local neighbor. In spite of dealing with the local neighbor structure information, the method does not fuse the structure information of multiple features for classification. Canonical correlation analysis (CCA) for feature fusion [10] maximizes the correlation of the multi-feature sets, which improve the classification performance by the correlation of the different feature sets. Nonetheless, the method does not process the interrelation in the same feature set. Multiview spectral embedding (MSE) [11] can use different ways for encoding different features, and project low dimension embedding for multi-view into the global coordinate to achieve physically meaningful embedding. However, this method only considers the low-dimensional embedding normalization of the global coordinate, does not mine the intrinsic structure of multi-feature through the structure fusion.

It is shown that the feature fusion method of the supervised learning is also the excellent performance. Multiple principal angle (MPA) [12] is a multi-set discrimination canonical correlation method, which considers both "local" and "global" canonical correlations by repeatedly learning multi-subspaces to obtain a global discriminative subspace. A new locality-preserving canonical correlation analysis (ALPCCA) [13] not only discovers the local manifold structure of data, but also enhances the discriminative power through learning label data. Semi-supervised multi-view distance metric learning (SSM-DML) [14] learns the multi-view distance measurement from multi-feature sets and from the labels of cartoon characters based on the umbrella of graph-based semi-supervised learning. Semi-supervised multi-view subspace learning (semi-MSL) [15] encodes different features in a unified space, which uses the discriminative information from labeled cartoon characters in the construction of local patches, and in these local patches, the manifold structure uncovered by unlabeled cartoon characters is made use of capturing the geometric distribution. Pairwise constraint based multi-view subspace learning (PC-MSL) [16] takes both intra-class and inter-class geometries into consideration. Consequently, the discriminative characteristic is effectively kept because it considers neighboring points, which have various labels. Restricted graph-based genetic programming (RGGP) [17] assembles 3D operators as graph-based combinations, and then evolves generation by generation by evaluating the average error rate of the classification accuracy, finally obtains the discriminative representation of RGB and depth information. However, these methods need to be supported by the label data, which of the collections usually is difficult. Therefore, in the paper, we focus on feature structure fusion of unsupervised learning for object classification. The proposed methods attempt to find the suitable metric for measuring the structure of the feature, and optimize to search the relation between these structures and fusion feature through feature structure interrelation, which is deduced based on manifold learning methods. In Fig. 1, CCA feature fusion of the multi-feature sets [10] (for example, three feature sets) and feature structure fusions are explained. Their most differences lie in the description and fusion of structure, which plays a key role for object classification.

Manifold learning [18-20] has the fruitful efforts at the measurement and preservation of the structure for processing data through the nonlinear projection. However, these methods do not involve the different metrics and the structure fusion. If these methods are directly used for the feature structure fusion, two questions occur as following.

a. The single metric (Euclidean distance) cannot adapt the structure measurement of the various features.

The different features have unique characteristics, so the metric of these features should suit various characteristics. However, in manifold learning, Euclidean distance is usually regarded as the basis metric, which is not enough for the structure measurement of these features.

b. The description of the structure fusion.

Manifold learning theory method only deeply studies on the preserving or mapping of the data structure, and not involves into the structure fusion. Nevertheless, structure fusion is a fundamental question, which plays a key role for mining the data structure and extracting the discriminative feature.

The proposed methods can appropriately deal with these questions for fusing the structure of the multi-feature.

Next, the paper is organized as following. Section 2 describes the metric and characteristic of the feature vector structure or feature vector space structure. Section 3 presents how to deduce the principle of the structure fusion based on manifold learning methods. Section 4 compares the experiment result of the structure fusion methods and other methods in shape analysis and human action recognition, and discusses the difference between the structure fusion method and the other fusion method. Lastly, a conclusion is summarized in Section 5.

2. Feature structure metric

The first question of the metric of the feature fusion is the local structure measurement of the feature, for example, distance, or similarity. The feature includes the vector or vector space, which decides the different metric method. In manifold learning, the local structure of the data is measured by Euclidean distance, but this distance is not suitable for measuring the structure of the feature vector, which follows the specific distribution information.

Moreover, it is not also satisfied for calculating the structure of the feature vector space. So which metric method selected is decided by the characteristic of the feature.

2.1. The metric of the feature vector

2.1.1. Euclidean metric

Euclidean distance is the most common metric, but it has the potential condition for the structure measurement of the vector.

a. The use of Euclidean distance requires the strictly matching relation between the vector elements, as is shown by the computation of Euclidean distance. In addition, it needs there is not the specific distribution between the vector elements. In other words, the vector distance is only related to the numerical value.
b. The numerical value of the vector should have the unified scale, and the numerical value and its sequence only have one meaning. The vector should distribute in the plan or hyperplan, which does not exit the bend in its space.

However, it is difficult that the vector data are satisfactory for above these conditions. In fact, the data not only obey that the specific distribution between the vector elements, but also distribute on the smooth and high-dimensional manifold.

2.1.2. χ^2 metric

χ^2 distance may measure the structure of the feature, which has the specific distribution. Its computation is shown as following [21].

$$d(B,C) = \frac{1}{2}\sum_{1\leqslant k\leqslant K}\frac{[h_B(k) - h_C(k)]^2}{h_B(k) + h_C(k)} \quad (1)$$

Here, B and C are respectively the feature vector. $h_B(k)$ is the distribution of k on B, and $h_C(k)$ is the distribution of k on C. χ^2 distance