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Shape classification by manifold learning in multiple observation spaces

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ABSTRACT

Manifold learning is a non-linear method with the aim of finding a constructive way to embed the data from a high-dimensional space into a low-dimensional one. The improvement of shape classification is the major approach in this paper which is based on the continuity in feature space in accordance with the continuity in semantic one. In this regard, a non-linear approach is employed to map the shape feature vectors to a new space while their semantics become similar with human opinion, the Euclidean distance between two feature vectors would be closed. Shapes are described by four contour-based and region-based techniques by the proposed method. In other word, they are described in four observation spaces. Furthermore, a parameter space is learnt from multiple observation spaces based on fusion of dissimilarities in a supervised manner. Experimental results show the validity and efficiency of the proposed approach for shape classification over a variety of standard shape datasets.

1. Introduction

Retina is a part of the central nervous system placed on the surface of eye. It is a multilayered light-sensitive tissue that lines the inside of the back of the eyeball and connects to the brain by the optic nerve. Images that are formed by the lens of eye are converted as electrical signals and transmitted to the brain as nerve impulses. In general, each image signal value is represented as a point in feature space. The following example shows different images of horse and dog selected from MPEG-7 Part B dataset [45]. As it can be seen, these points are distributed in three-dimensional feature space without structural representation that indicates a semantic dependency between them. However, the conceptual mapping of these points would be put in the same cluster by human mind. The dimensions of the conceptual structure are far less than that of the observation feature vectors.

In order to improve shape classification, samples that belong to a same class will have less Euclidean distance than others. As is shown in Fig. 1, the proper extraction of parameters space improves the accuracy of classification.

However, intrinsic dimensions are not structured in a linear manner for extracting from the samples in feature space. Therefore, linear feature extraction methods such as Principal Component Analysis (PCA) are not properly able to discover the latent structures [67]. So that non-linear feature extraction algorithms known as manifold learning would be appropriate to discover the intrinsic dimensions by the use of graphs and some new metrics like geodesic distance.

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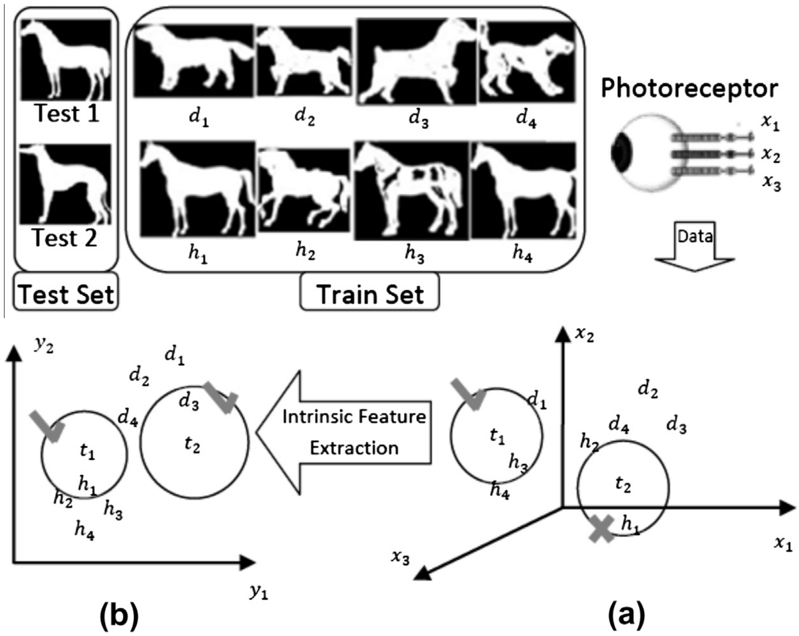

Fig. 1. Shape classification by K-NN $k = 1$. (a) Feature vectors in observation space and (b) feature vectors in parameter space.

In this paper, a supervised manifold learning method is proposed for shape recognition. The proper use of dissimilarities in multiple feature spaces is the main innovation in this research. Although there are some interesting works on supervised manifold learning, the fusion of multiple feature spaces has not yet been studied.

The manifold learning method proposed in this paper is based on fusion of normalized dissimilarities from multiple spaces. Euclidean distance between samples in parameter space is closer to the conceptual distance rather than that of in multiple observation spaces. The experimental results on some shape datasets indicate the validity and efficiency of the proposed method.

The paper is organized as follows. Section 2 presents a brief review of the manifold learning methods. In Section 3, the approach is introduced based on supervised manifold learning on multiple spaces. Section 4 presents the experimental results on some standard datasets. Finally, concluding remarks and further works are discussed in detail.

2. Manifold learning

High-dimensional data analysis has become a significant research interest due to the emergence of new applications such as bioinformatics, multimedia retrieval and remote sensing. Research on extracting meaningful information from high-dimensional data spaces is currently one of the main interests. Different approaches in machine learning, statistics and mathematics have been introduced. "Curse of dimensionality" was originally discussed by Bellman in 1961 [9]. The term was applied to the problem caused by the rapid increase in volume with adding more dimension to a specified space. The small sample set and high dimensionality problem are two major challenges in many computer vision applications such as Content Based Image Retrieval (CBIR) [71]. This section is organized as follows. Section 2.1 introduces the manifold learning methods and overviews them as two unsupervised and supervised categories. Section 2.2 overviews machine vision applications based on manifold learning methods.

2.1. Manifold learning methods

In general, a large number of features cause the increase of complexity in data analysis and reduce the performance of learning methods such as classification and clustering [71]. Therefore, dimensional reduction becomes an important issue. The most popular approaches to feature reduction are classified into two categories; feature selection and feature extraction. In feature selection, sample τ with d features is generated from sample x with D features where $d < D$. Traditional feature selection methods attempt to find a global optimal subspace. A comprehensive overview of various aspects of feature selection methods has been introduced in [52]. In many applications, different clusters of data may have different subspaces. The aim of hard subspace clustering is to find the exact subspace for each cluster by giving 0 or 1 to all features. However, soft subspace learning assigns a range of values between 0 and 1 to all the features for each cluster [49]. [58,38] took a comprehensive overview of subspace learning methods. It is necessary to mention that in feature extraction, the features