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Express Paper

Intraclass Identifiable Region Detection

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Abstract: In this paper, we propose a novel method for comparing the shape of similar objects. From the viewpoint of linear algebra, we turn this identifiable region detection problem into a low-rank submatrices searching process, and solve it with biclustering. Comparing with traditional cluster analysis, our method looks for structural information on both object index and local shape dimensions, which leads to more detailed local comparison results. The proposed method is evaluated with real world data with satisfactory results, which verifies the effectiveness of our method.

Keywords: intraclass shape analysis, identifiable region, low-rank matrix, biclustering

1. Introduction

Shape analysis is one of the most fundamental problems in computer vision. In this paper, we focus on the problem of intraclass shape comparison. More specifically, we are interested in detecting "feature" regions that make two sub-categories different from each other, such as the highlighted swallowtail regions shown in **Fig. 1**. In this paper, we call these kind of regions the *identifiable* regions.

1.1 Interclass and Intraclass Problems

Generally speaking, depending on the types of target objects, the problem of shape analysis can be further divided as interclass analysis and intraclass analysis. The former issue crosses over objects without any similarity prerequisite; while the latter issue focuses on the analysis on those targets belong to the same category. Since objects from the same class usually have similar shapes and structures, finer comparison is required for intraclass analysis.

Figure 2 shows two different data sets, belonging to interclass and intraclass problems respectively. Notice that these two different kinds of problems actually stay in different levels of analysis: while in interclass analysis we pay more attention to recognition, which is to solve the problem "what is this?," intraclass analysis focus on more detailed shape comparison, e.g., "How to further divide them into sub-groups? What is the difference between them?."

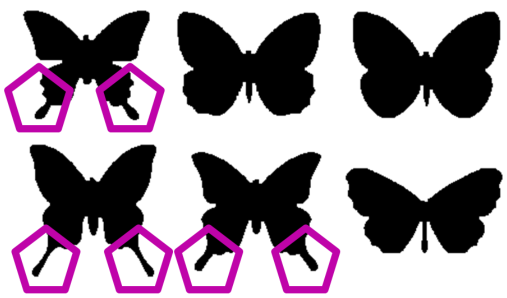

Fig. 1 Silhouettes of butterfly. The highlighted swallowtail regions make the *Papilio* samples different from the others.

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1.2 Motivation

Given a group of shapes for comparison, denoted as $\{S_i\}_{i=1}^{N}$, the traditional method is to find a proper metric $d : S \times S \rightarrow \mathbf{R}$ to evaluate the distance between them. This metric can be used to form a distance matrix, like the one shown in **Fig. 3**.

However, if we want to know the details about shape differences, the previous scalar evaluation will not be enough. For

Fig. 2 Two data set of 2D silhouettes images. The top two rows constitute one data set, where samples are totally different objects from each other. This leads to an interclass problem. The bottom two rows form the other data set, where samples are all butterflies, with slightly different shapes. This belongs to the intraclass analysis. These images are from a large binary image database collected by the LEMS Vision Group at Brown University.

instance, given silhouettes from different kinds of butterfly, as shown in Fig. 1, we would like to detect the most identifiable regions that cause these subcategories differ from each other.

Compared with general shape comparison problems, this intraclass shape analysis enjoys better semantic explanation and higher processing accuracy, which can be used in a wide range of applications, such as biometrics, medical diagnosis, etc. Taking 3D face recognition as an example, where 3D geometry of the facial part is captured and then compared with others, the proposed method can be used to detect the most identifiable regions between different groups, e.g., Asians and Europeans. This detection result can be further used as prior knowledge to guide the recognition system, improving its accuracy.

1.3 Related Work

Based on local shape descriptors and effective indexing, several partial matching methods are proposed, such as the studies in Refs. [1], [9]. Notice that these methods highly rely on the ability of local descriptors to distinguish shapes as well as the selection of proper scales. These weaken the ability of these kind of methods, especially in 3D shape comparison case. Since the current state-of-the-art local descriptors, e.g., *spin images* [10], is still not that effective to distinguish local shapes.

Another branch of methods to analyze a set of shapes is the statistical shape analysis [6], where statistics are measured to describe geometrical properties from similar shapes or different groups. Usually principal component analysis (PCA) [11] is used to analyze the shape variability. It is easy to obtain average shape as well as shape differences with this kind of analysis.

1.4 Contribution

We present a quantitative method to compare similar shapes. A reinforced scheme to detect identifiable regions are proposed. This is a novel and interesting attempts to analyze similar objects from the viewpoint of linear algebra. Different from traditional methods, our approach looks for structural information on both object index and local shape dimensions, which leads to more detailed local comparison results.

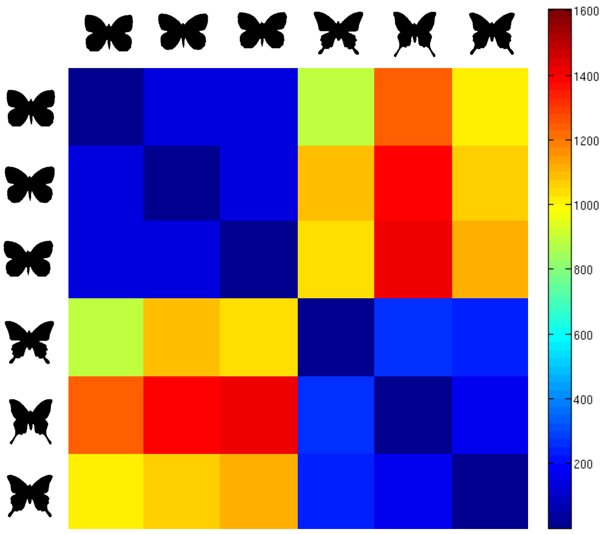


Fig. 3 An example of distance matrix.

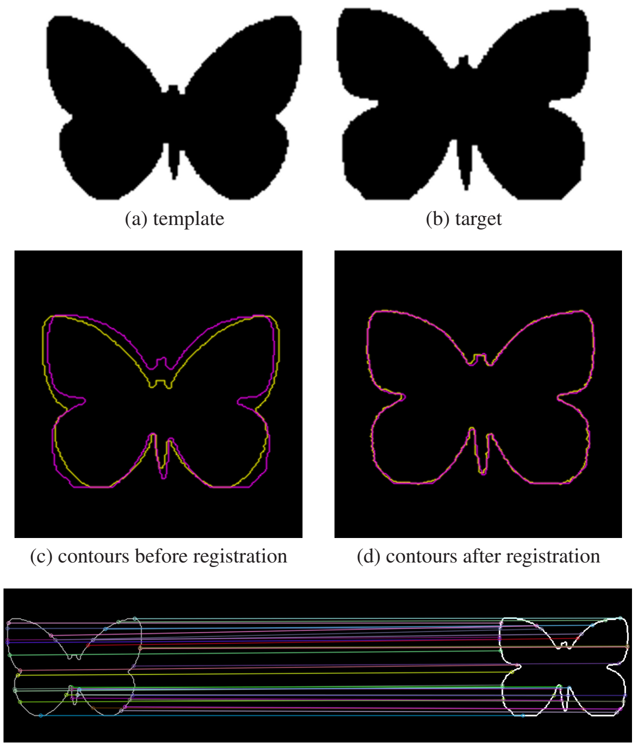
The remainder of this paper is organized as follows: we will first introduce a non-rigid registration method with local structures kept in Section 2; an identifiable region detection method based on biclustering is introduced in Section 3; and then we show experimental results as well as discussions.

2. Shape Matching

One essential part of the proposed comparison method is shape registration. While source object is deformed to target shape, the differences between them will be revealed.

Here we choose a non-rigid registration method introduced in Ref. [8]. Compared with other shape matching method, such as Refs. [12] and [2], this method is more appropriate for our problem. This is mainly because that common methods usually focus on reducing the residuals of registration only, without considering of keeping local structures. This may lead to inaccurate correspondences between objects and hurt the performance of the later comparison. On the contrary, based on the observation that similar objects usually have very similar local structures, the chosen registration method uses local rigid transformations to guide a underlying free-form deformation (FFD, introduced in Ref. [15]). Due to this attribute, local structures will be kept during the registration.

Moreover, the registration process also provides us a way to find correspondences between similar objects. Based on the registered result, corresponding points can be obtained by adopting the nearest neighbor point search. A discussion about the nearest neighbor search problem is given by Ref. [18]. **Figure 4** shows

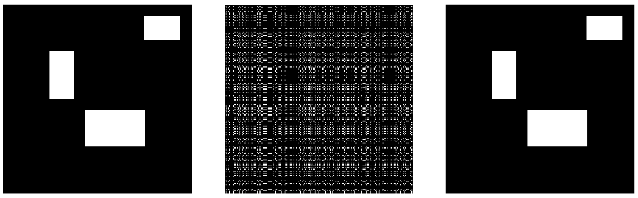


(a) template (b) target

(c) contours before registration (d) contours after registration

(e) matching result

Fig. 4 An example of shape matching. The correspondences are obtained via the nearest neighbor search based on the registered shape (d). A common method to accelerate this search is to use k-d tree data structure.



(a) original (b) disturbed (c) recovered

Fig. 5 A demonstration of the biclustering process. We first synthesize a binary matrix with clear structures—three white blocks shown in (a), and then randomly reorder it, demonstrated as (b). After proper operations to re-order both rows and columns of the disturbed matrix, its original version can be recovered via biclustering, as shown in (c).

an example of shape matching.

3. Identifiable Region Detection

Traditional cluster analysis can only provide overall grouping information, such as the dendrogram generated by hierarchical clustering. In this section, we will introduce a method to automatically detect identifiable regions among a group of shapes.

3.1 Biclustering Methods

Recently, biclustering techniques, such as studies in Refs. [4], [5], [7], [13], [14], were proposed for revealing submatrices showing unique patterns, e.g., a submatrix with low numerical rank [16]. Different from traditional approaches, these methods simultaneously discover row and column groups and the detected biclusters may correspond to arbitrary subsets of rows and columns, such as those white rectangles shown in **Fig. 5**.

In our problem, we choose the biclustering method proposed in Ref. [4]. Based on the fact that good clustering usually leads to a few homogeneous blocks in data matrix, this method makes use of lossless data compression to decompose a binary matrix into disjoint row and column groups. Compared with other biclustering method, such as Ref. [5], numbers of row and column groups are no longer needed to be specified in this method. For further information about biclustering method, a survey given by Ref. [17] as well as the above references are suggested.

3.2 Detecting Identifiable Region via Biclustering

Based on the correspondences we obtained by shape matching, we start to find feature regions that distinguish different subcategories from each other.

Suppose there are N targets, each of which has M sampling points with known correspondences. We first generate a N-by-M matrix D to record detailed differences at all points between these targets and a certain object, e.g., the average shape. Here the difference means the displacement between corresponding point pairs. In order to emphasize the most notable regions, we use the robust PCA method introduced in Ref. [3] as well as binarization to filter this matrix, highlighting significant regions.

We then search for notable similarities along not only the dimension of the object index but also the dimension that corresponds to spatial sampling points. Due to the fact that identifiable regions lead to regular structures in the difference matrix we generated, we turn this partial similarity searching problem into a low-rank submatrix detection process, which can be solved by biclustering method. Algorithm 1 shows the whole flow of our proposed method.

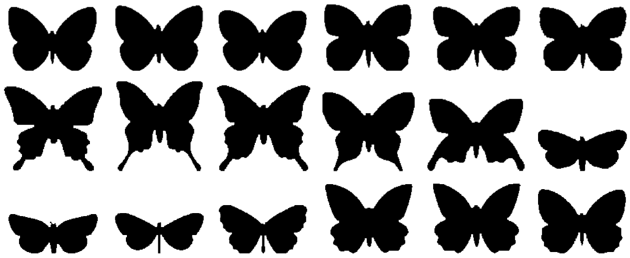


Fig. 6 A butterfly data set from a large silhouette image database collected by the LEMS Vision Group at Brown University.

Algorithm 1 Identifiable Region Detection

Input: a group of similar objects $\{S_i\}_{i=1}^N$

Obtain dense correspondences $\{P_{S_i}\}_{i=1}^N$ between $\{S_i\}_{i=1}^N$

Calculate the average $\overline{P_S} = \frac{1}{N}\sum_{i=1}^N P_{S_i}$

for $i = 1 \to N$ **do**

Evaluate the displacements at every corresponding points: $\mathbf{d}_{S_i} = |P_{S_i} - \overline{P_S}|$

end for

Form the displacement matrix $D \doteq [\mathbf{d}_{S_1}|\cdots|\mathbf{d}_{S_N}]^T$

Filter D to matrix A in order to highlight features

Binarize A to matrix B by thresholding

Adopting biclustering on B to find notable regions $\{R_t\}_{t=1}^K$

Output: $\{R_t\}_{t=1}^K$

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4. Experiments

From a large binary image database collected by the LEMS Vision Group at Brown University, we selected a butterfly silhouette data set containing 18 samples, as shown in **Fig. 6**. Samples from several subcategories are included, such as Papilio. The following experiments are mainly adopted on this data set.

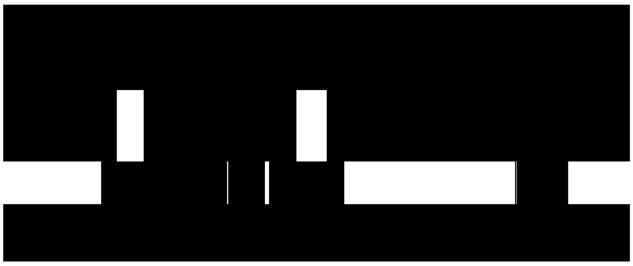
We adopted the proposed method to the butterfly data set, with 300 sampling points for shape matching, and the standard hyper parameter values [*1]. **Figure 7** shows the effectiveness of the low-rank matrix filtering we designed. Two low-rank submatrices are found in the biclustering process, as shown in **Fig. 8**, which correspond to two different subcategories respectively. Notice that the desired result similar to Fig. 1 is obtained.

5. Summary

In this paper, we focus on the problem to compare similar shapes. We turn the identifiable region detection problem into

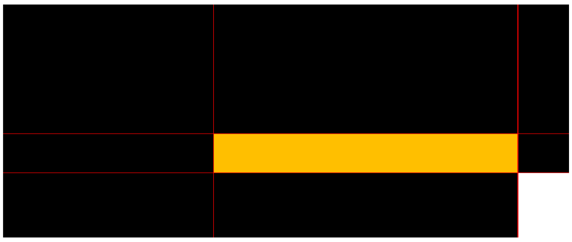
*1 The regularization coefficient λ in RPCA was set to 1, and the median was used as threshold for binarization.

(a) Original binary representation matrix



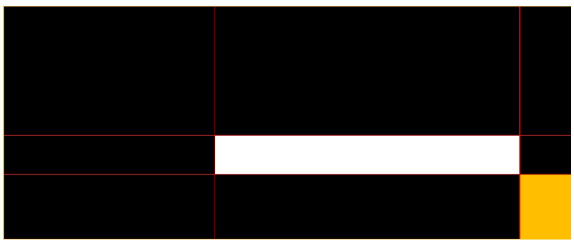
(b) Representation matrix after RPCA filtering

Fig. 7 The effect of RPCA filtering. Clearer result is generated.



(a)

(b)



(c)

(d)

Fig. 8 The two detected low-rank submatrices (yellow blocks in the figure) and their corresponding regions (highlighted in red color). (a) and (c) are the reordered version of the matrix shown in Fig. 7 (b), given by the biclustering process.

a low-rank submatrices searching process, and solve it with the biclustering algorithm. Based on corresponding points obtained from shape matching, we combine biclustering with low-rank matrix analysis to detect identifiable regions. Compared with the traditional cluster analysis, our method searches for structural information on both object index and local shape dimensions, which leads to more detailed comparison results.

The proposed methods are evaluated with real world data. Satisfactory results are achieved, which verifies the effectiveness of our study. This identifiable region detection method can be easily extended to handle 3D objects as well.

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