A-019

Image Retrieval Using Shape Recognition

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Abstract

In this research, an image retrieval system which utilize a shape invariant and a geometric method for retrieving similar shapes is proposed. The system consists of three steps. First, the images are retrieved using the shape invariant $F(P)$, which computed by compressing the distance distribution of n boundary points of a polygonal P, and its discretized called $\sigma(F(P))$. The signature invariant $\sigma(F(P))$ enables images which are $\sigma(F(P)) \approx \sigma(F(Q))$ to be retrieved from a hash table efficiently. Finally, the geometric pattern matching method is used to remove irrelevant images retrieved.

1 Introduction

In pattern recognition technology, such as character and fingerprint recognition systems, shape-based feature information has been extensively used in designing efficient systems excepts an image retrieval system. The current commercial systems (Google and Yahoo) retrieve images according to associated metadata and label attached to images [1]. Due to the increased in the number of images, an image annotation [3] is needed in order to automatically assign label according to color and texture features extracted from an image. However, we found that the quality bound of using these features restricts the quality of the label. Therefore, a "shape" feature which is a significant feature for human to recognize an object can be utilized to improve the quality of the label. However, the shape is difficult to handle in a computerized information retrieval system.

In computational geometry, geometric pattern matching algorithms, such as Hausdorff distance, are used to compute a similarity between two objects. By using the geometry pattern matching method, the similarity between a query object Q and each object P in the database is computed. The problem is, therefore, the $O(Np(n))$ time complexity where N is the database size and $p(n)$ is the time complexity for the geometric pattern matching. Particularly N is huge, thus, this time complexity is not acceptable to an information retrieval system.

Our objective is an image retrieval system which the query time is independent of N or logarithmically N. In this research, we proposed an image retrieval system which is able to cope with the huge query time of geometric pattern matching by reducing the size of the data before computing similarity using the geometric pattern matching. In this research, the data is retrieved from an efficient search data structure according to an invariant description that is able to capture the characteristic of a shape and also invariant to noise and the rigid transformation. Moreover, if the two objects are similar then the invariant description of the two shapes must also be similar. Such description is called a *shape invariant.*

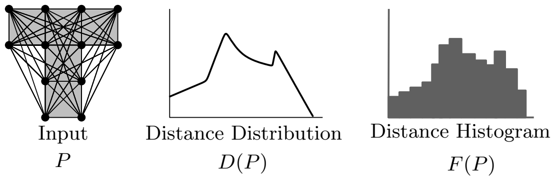

Figure 1: Shape invariant

Among the shape invariants, a distance-based shape invariant is a basic one which was applied for pattern matching of three dimensional objects [4, 2]. The distance-based shape invariant is able to capture the shape to some extent. Except the difficulty that is an existence of a *homometric pair* of different objects, which have the same the distance set $D(P)$ and $D(Q)$ [5]. Therefore, the shape invariant cannot completely classify shapes.

In this research, we proposed an image retrieval system which is able to overcome the time complexity and the homometric pair problems.

2 Shape-based Image Retrieval

Our proposed method consists of three main steps: Preprocessing, Screening, and Refining as shown in Figure 2.

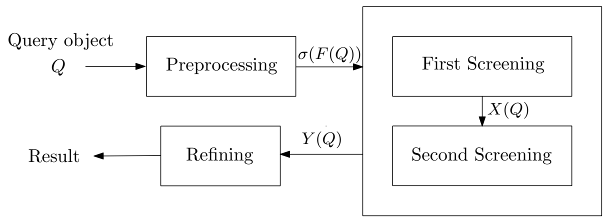

Figure 2: Our proposed three steps image retrieval system

In the preprocessing step, the shape invariant $F(P) = \{p_1, p_2, \ldots, p_k\}$, where p_i is the number of distances in the i-th bin, of each object in the database is computed by compressing the distance set $D(P)$ of $n(n-1)/2$ pairwise distances using a distance histogram as shown in Figure 1. Then a *signature invariant* $\sigma(F(P))$ is computed by discretizing the shape invariant $F(P)$ using a log-scale which represents a key

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in the hash table. The time complexity for the preprocessing step is $O(Nn^2)$ where N is the database size and n is the number of boundary points of P.

To retrieve similar objects according to the query object Q, the set of similar objects $X(Q) = \{P : \sigma(F(P)) = \sigma(F(Q))\}$ is retrieved in the first screening process. In the second screening, the candidate set $Y(Q)$ which contains K similar objects is selected according to L_1 distance of $F(Q)$ and $F(P)$. The time complexity for retrieving the set $X(Q)$ from the hash table is $O(1)$ and $O(k|X(Q)|)$ for computing L_1 distance in order to select K candidate set $Y(Q)$. Due to the existence of the homometric pair, the geometric pattern matching is used to remove irrelevant objects from $Y(Q)$ in the Refining process. By reducing the candidate size, the time complexity of using the geometric pattern matching become $O(Kp(n))$ where $K \ll N$.

The result from the first screening which contains some irrelevant objects is shown in Figure 3(b) whereas such objects are removed after applying the geometric pattern matching as evidence in Figure 3(c). From the experimental result, we also found that if $|X(Q)|$ and K are too small then relevant image may not be included since the screening process. From this observation, we proposed a more precise shape invariant.

Figure 3: (a) Query object, (b) Result from the screening process, (c) Result from our image retrieval system

3 A Refinement of Distance Distribution

The distance distribution of classified distances was presented in [2]. The distances are classified according to the segment defining the distance that are interior ($d_{interior}$), exterior ($d_{exterior}$), and mixed (d). In this research, we considered the shape invariant computed from the distribution of two parameters which are the distance d and R_{in} ($R_{in} = d_{interior}/d$).

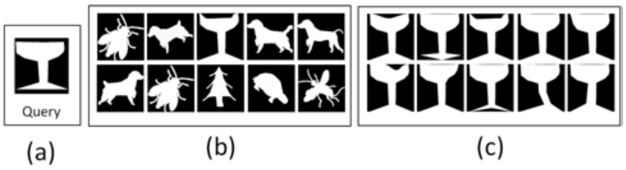

Figure 4: (a) A query object, (b) Retrieved images using the distance distribution, and (c) Retrieved images according to the classified distances

From the experimental result, the two different objects which are similar according to L_1 distance is shown in Figure 5(b). By using our method, the two-parameter distance histogram of Fly and Glass are different as presented in Figure 5(c) and (d) respectively. Therefore, the images retrieved from the query in Figure 4(b) using the distance distribution is improved as in Figure 4(c).

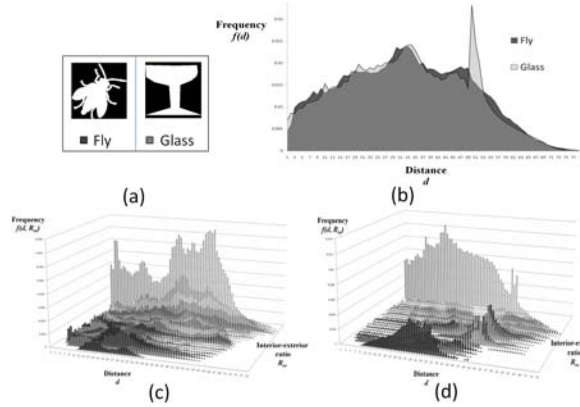

Figure 5: (a) A query object, (b) Distance distribution of (a), (c) Distance distribution of classified distances of Fly, and (d) Distance distribution of classified distances of Glass

Our proposed distance distribution is able to classify the shapes. However, applying the two-parameter shape invariant in the efficient search data structure such as locality preserving hash is difficult.

4 Conclusion

In this research we proposed an image retrieval system which applies the distance-based shape invariant and the geometric pattern matching. Our proposed system is able to cope with the homometric pair problem and the huge query time while preserving accuracy.

In the future, we would like to obtain more precise candidate size $X(Q)$ as well as an efficient query time. So, a more powerful shape invariant which is able to be applied in the efficient search structure, such as a locality sensitive hash, is needed.

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