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SHAPE SIMILARITY ANALYSIS FOR IMAGE RETRIEVAL BY LOCALLY CONSTRAINED MIXED DIFFUSION

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ABSTRACT

Similarity analysis is a powerful tool for shape matching/retrieval and computer vision tasks. Different measures specialize on different aspects of the data. The problem of improving retrieval accuracy by systematically fusing several different measures. This paper proposes the locally constrained mixed diffusion method, which partly fuses the given measures into one and propagates on the resulted locally dense data space. Furthermore, the use of self-adaptive neighborhood automatically determines the appropriate size of the neighborhoods in the diffusion process, with which the retrieval performance is comparable to the best manually, tuned kNNs. The superiority of approach is empirically demonstrated on both shape and image datasets. First a fully connected graph is created. Then it is simplified using a kNN graph. The optimal number of neighbors is finding out using a dominant set. The neighborhood structure of each data points are found out using dominant set. Finally analysis is done.

INDEX TERM: Scale Invariant feature extraction (SIFT), Self Adaptive Neighborhood (SAN), Locally Constrained Mixed Diffusion (LCMD), Support Vector Machine (SVM), K Nearest Neighbour (kNN).

1. INTRODUCTION

Shape retrieval tasks require that we recover from a database a set of shapes which are most similar to a query shape. An important component of most retrieval systems is the distance measure used to measure shape similarity. Shape context method is used for shape similarity analysis. SC encodes the global information of a shape into a histogram. The Euclidean distance is replaced using geodesic distance. To describe shapes Poisson equations is used. Articulation-Invariant Representation is used for analyzing shapes. Post processing and rank

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aggregation were used for shape analysis. The similarities between the shapes are identified using Locally Constrained Mixed-Diffusion method. The self -adaptive neighborhood for each shapes were created. First a complete directed graph is created, and then it is simplified using kNN graph. The optimal numbers of neighbors are found out using a dominant set. A dominant set is a subset of the data which corresponds to a maximally cohesive cluster. The neighborhood structure of each data points are found out using dominant set.

Moreover, the pair wise similarity or distance defined on most conventional representations is often incapable of capturing category-level information across classes. To exploit these high-level relationships, it requires more sophisticated analysis of shapes. Recently, many learning-based methods have been proposed to conquer the two above-mentioned problems in shape retrieval. These methods exploit the underlying structure of the datasets to improve the retrieval accuracy obtained by existing ranking approaches. Other approaches such as rank aggregation concentrate on integrating different rankings into a single more accurate measure. In this work, consider the problem of improving retrieval accuracy by fusing different similarity or distance measures. Because different measures specialize on different aspects of the data, the intuition here is that better performance might be achieved by combining multiple complementary measures. Our goal is that in an integrated ranking system, an instance being ranked high in all measures should be at the top. At the same time, an instance being ranked high in a particular measure also deserves a position in the retrieved list. Shape retrieval/matching is a very important topic in computer vision. The recent progress in this domain has been mostly driven by designing smart features for providing better similarity measure between pairs of shapes. In this paper, provide a new perspective to this problem by considering the existing shapes as a group, and study their similarity measures to the query shape in a graph structure. The method is general and can be built on top of any existing shape matching algorithms. It learns a better metric through graph transduction by propagating the model through existing shapes, in a way similar to computing geodesics in shape manifold. However, the proposed method does not require learning the

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shape manifold explicitly and it does not require knowing any class labels of existing shapes.

2. EXISTING SYSTEM

Shape context method is used for shape similarity analysis. SC encodes the global information of a shape into a histogram. The Euclidean distance is replaced using geodesic distance. To describe shapes Poisson equations is used. Articulation-Invariant Representation (AIR) is used for analyzing shapes. Post processing and rank aggregation there used for shape analysis.

3. PROPOSED SYSTEM

The similarities between the shapes are identified using Locally Constrained Mixed-Diffusion method. The self adaptive neighborhood for each shapes there created. First a complete directed graph is created, and then it is simplified using kNN graph. The optimal numbers of neighbors are found out using a dominant set. A dominant set is a subset of the data which corresponds to a maximally cohesive cluster the neighborhood structure of each data points are found out using dominant set. Finally using these shape or image analyses is done. This algorithm can be extended to other similarity measures such as image similarity. Accuracy of the algorithm is high when compared to the previous works.

4. DESIGN

4.1. ARCHITECTURE DIAGRAM

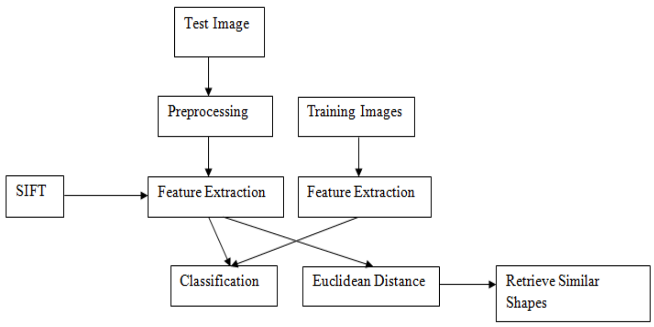

Figure1: System Architecture

4.2. ALGORITHMS

4.2.1. Scale-Invariant Feature Transform

It is an algorithm in computer vision to detect and describe local features in images. For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted from the training image be detectable even under changes in image scale, noise and illumination. Such points usually lie on high-contrast

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regions of the image, such as object edges. Another important characteristic of these features is that the relative positions between them in the original scene shouldn't change from one image to another. First the extreme is calculated for the Scale-Space. Then the key points are localized. The nearby points are interpolated. The Low contrast key points and the edge responses are eliminated.

4.2.2. SVM Classification

Support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Classification accuracy is computed. SVM maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed. Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category. This hyper plane which maximizes the margin is called the optimal separating hyper plane and the margin is defined as the sum of distances of the hyper plane to the closest training vectors of each category. Expression for hyper plane is

$w.x+b = 0$

x – Set of training vectors

w – Vectors perpendicular to the separating hyper plane

b – Offset parameter which allows the increase of the margin

Margin is $d1+d2$

Kernel function is used when decision function is not a linear function of the data and the data will be mapped from the input space through a non linear transformation rather than fitting non-linear curves to the vector space to separate the data. With an optimal kernel function implemented in SVM model, the classification task is able to scale high dimensional data relatively, tradeoff between classifier complexity and classification error can be controlled explicitly.

Euclidean Distance

The Euclidean distance or Euclidean metric is the "ordinary" distance between two points that one would measure with a ruler, and is given by the Pythagorean formula. By using this formula as distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. Older literature refers to the metric as

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Pythagorean metric. This is used to find the similarity between the image that the give and the image the images in the dataset.

5. IMPLEMENTATION

5.1. PREPROCESSING

In preprocessing method median filter is used to remove noise from the input images. It is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering is very widely used in digital image processing.

5.2. LOCALLY CONSTRAINED MIXED DIFFUSION METHOD

The directive graphs are created. They are then combined using KNN graphs. Useful information of some measures may be submerged into the background during the construction of graphs. A Markov mixture model was proposed, which is able to keep the information of all measures of the data. Features are extracted from the image.

5.3. SELF ADAPTIVE NEIGHBORHOOD

To automatically determine the optimal number of neighbors Dominant set is used. A dominant set is a subset of the data which corresponds to a maximally cohesive cluster. To reveal the neighborhood structure of each data point, Self-Adaptive Neighborhood (SAN) method is used. The extracted features from the train images and the test images are passed into the classifier. The classifier matches the Test image feature with the Train image features. Using the True label the classifier classifies the image.

5.4. AFFINITY MATRIX

The provided pair wise distance matrices need to be converted to affinity matrices before propagation. Moreover, the scale differences between distance matrices should be taken into account as they may cause problems. To measure the minimum distance between the features Euclidean distance is measured. The images are retrieved based on the minimum Euclidean distance between them.

5.5. ANALYSIS

The performance of the Classifier is analyzed. Time complexity and average number of iterations calculated. The LCMD+SAN method obtains a bull's eye score of 100%.

6. CONCLUSION

This paper proposes a effective method to analyze the similarity between

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shapes using unsupervised learning methods. It's introducing kNN graph to find the dominant set of the neighbors. The images are classified based on the features extracted from the image and a clustering based approach for finding similarities in the given datasets. Euclidean distance is measured to retrieve the similar shapes. Algorithm shows high performance compared to the previous works.

7. FUTURE WORK

In Future the algorithm can be extended to retrieve face images by extracting additional futures such as Colour histogram features and LDA features. The same algorithms are used as in the proposed system additionally Colour Histogram features and LDA features are extracted from the training set images and the test images. The extracted features are matched and similar features are retrieved by measuring the Euclidean distance.

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