Efficient Image Mining Techniques using Spatial Information

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Abstract: Image mining involve transforming Image in to data set and applying data mining techniques on mage data set to reveal hidden knowledge. Spatial information in image is used to build high-level content models, used by Decision makers, analysts' interpreters. Spatial co orientation patterns, directional spatial relation among objects are very useful in analyzing image properties .In Image, Spatial relationship is obtained in terms of distance, topology, direction, constraint etc. spatial domain object-based approaches is used on geometrical information of the scene or object in the image classification. Geometrical information of the scene or object in the image could also be considered in the classification process by using object-based approaches in the spatial domain. The spatial properties are studied and used in mining image data to obtain efficient searching, faster retrieving. Spatial data mining minimizing the misclassification reduces the overlapping in clustering. A study has been made to know the different spatial techniques applied on images and its usage

Keywords: Spatial relationship, classification, Geometrical information

1. Introduction

As the technology improves a bulk of images are available like high resolution satellite image, camera captured image, web image, medical images and so on. There has to be some way to use these available data for analysis and to discover knowledge hidden in images. Research work is going on and improvements are done on the existing methods.

Image has spatial relationships: distance, topological, and directional relationship [1] [3]. Pattern growth approach, for mining co-orientation meaningful patterns from spatial or image databases are important. Several studies have focused on mining spatial co-location patterns, locating together closely. [1]The proposed model automatically identifies image areas for relationships relative to several reference objects and uses this information as spatial constraints for contextual classification and retrieval using Bayesian decision rule.

Spatial fuzzy c-mean clustering algorithm can perform unsupervised clustering and classification of image data using both the feature space information and the spatial contextual information. When dealing with high spatial resolution images, object-based approaches are generally used in order to exploit the spatial relationships of the data.

In the following section a description of different Spatial techniques applied on various image applications are explained. Efficient Technique can be applied according to the requirement. It can also be used to develop new spatial mining algorithms, Refining existing algorithms.

An approach for unsupervised Constraints on the clustering based on Genetic Algorithms (GAs) is used for unsupervised method. Bayesian framework [2] that uses spatial information for classification of high-resolution images is developed. First, spectral and textural features are extracted for each pixel. Then, these features are quantized and are used to train Bayesian classifiers with discrete non-parametric density models. Next, an iterative split-and-merge algorithm is used to convert the pixel level classification maps into contiguous regions.

Recent research work calculates the expected distance by calculating the weighted average of the pair-wise distances among samples of two uncertain objects. However the pair-wise distance calculations take much longer time than the former method. Hence paper [8], we propose an efficient method Approximation by Single Gaussian (ASG).

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2. Related Work

Image mining is an important task to discover interesting and meaningful patterns from large image databases. Spatial co orientation is considered in [1], spatial co-orientation patterns refer to objects that frequently occur with the same spatial orientation, e.g. left, right, below, etc., among images. For example, an object P is frequently left to an object Q among images. We utilize the data structure, 2D string, to represent the spatial orientation of objects. An efficient algorithm is proposed that is, pattern-growth approach, for mining co-orientation patterns.

To discover the spatial co-orientation patterns from a database of symbolic pictures, we employ the 2D string representation to represent symbolic pictures as in indexing of image retrieval [2]. In the 2D string approach, first, for each object in an image, the ortho-relation objects with respect to other objects are generated. The ortho-relation objects are used to characterize the relative spatial location with respect to other objects. Then, the reference points which are the central points of each ortho-relation objects constitute the symbolic picture. At last, the symbolic picture which preserves the relative spatial relationship is encoded as a 2D string a Apriori-based algorithm is used to discover the spatial co-orientation patterns [10] as |similar to prefix span as in[8] for mining sequential pattern.

Efficiency of proposed two approaches is measured by the number of images, the total number of objects, and average number of objects in an image and the minimum support the synthetic data generator developed by IBM Almaden Research Center to generate transactions is utilized, The paper regarding pattern growing is revised, published [6] and its application is extended to Analyzed tool for spatial cognitive development. Pattern-growth algorithm performs more effectively than Apriori-based algorithm.

A model is built using directional spatial relationships among objects [2] for contextual classification and retrieval .The proposed model automatically identifies image areas for relationships relative to several reference objects and uses this information as spatial constraints for contextual classification and retrieval using Bayesian decision rule. The model also supports dynamic queries by using directional relationships as spatial constraints to enable object detection based on the properties of individual objects as well as their spatial relationships to other objects.

Experiments using high-resolution satellite imagery showed that the Bayesian decision rule that incorporated spatial information significantly decreased the amount of commission among spectrally similar classes. Retrieval experiments also showed that the proposed models produced more intuitive results and higher precision than other approaches in dynamic query scenarios with spatial constraints.

Comparative experiments using high-resolution satellite imagery illustrate the flexibility and effectiveness of the proposed framework in image mining with significant improvements in both classification and retrieval performance.

Spatial clustering [3] has been an active research area in Spatial Data Mining (SDM). There are many methods for spatial clustering, but few of them have taken into account constraints that may be present in the data or constraints on the clustering. In [3] discuss the problem of spatial clustering with obstacles constraints and propose a novel spatial clustering method based on Genetic Algorithms (GAs) and KMedoids, called GKSCOC, which aims to cluster spatial data with obstacles constraints. The GKSCOC algorithm can not only give attention to higher local constringency speed and stronger global optimum search, but also get down to the obstacles constraints and practicalities of spatial clustering. The results on real datasets show that the algorithm performs better than the IKSCOC (Improved Spatial Clustering with Obstacles Constraints Based on K-Medoids) algorithm in terms of quantization error. Techniques have focused on the performance in terms of effectiveness and efficiency for large databases. Spatial clustering with constraints has two kinds of forms [1]. One kind is spatial clustering with obstacles constraints, such as bridge, river, and highway etc. whose impact on the result should be considered in the clustering process of large spatial data. The other kind is spatial clustering with handling operational constraints [2], it consider some operation limiting conditions in the clustering process. Discussion is only for spatial clustering with obstacles constraints. Three clustering algorithms for clustering spatial data with obstacles constraints have been proposed very recently: COD-LARANS [3], AUTOCLUST+ [4], and DBCluC [5]-[8]. CODCLARANS algorithm only gives attention to local constringency. AUTOCLUST+ algorithm builds a Delaunay structure to cluster data points with obstacles costly and is unfit for a large number of data. DBCluC cannot run in large high dimensional data sets etc.

In this method attention to higher local constringency speed and stronger global optimum search is given, and also get down to the obstacles constraints and practicalities of spatial clustering. The results of the experiments on real datasets show that the GKSCOC algorithm performs better than the IKSCOC algorithm in terms of quantization error. The drawback of GKSCOC algorithm is a comparatively slower speed in clustering. But its achievements will have more practical value and extensive application prospect.

As there is an increase in the amount and resolution of remotely sensed imagery it necessitates in the development of automatic processing and classification system [4].

A Bayesian framework that uses spatial information for classification of high-resolution images is developed. First, spectral and textural features are extracted for each pixel. Then, these features are quantized and are used to train Bayesian classifiers with discrete non-parametric density models. Next, an iterative split-and-merge algorithm is used to convert the pixel level classification maps into contiguous regions. Then, the resulting regions are modeled using the statistical summaries of their spectral, textural and shape properties, and are used with Bayesian classifiers to compute the final classification maps. Experiments with three ground truth data sets show the effectiveness of the proposed approach over traditional techniques that do not make strong use of region-based spatial information. Proposed region level features and Bayesian classifiers performed better than the traditional pixel level classification techniques. Even though the numerical results already look quite impressive, we believe that selection of the most discriminative subset of features and better segmentation of regions will bring further improvements in classification accuracy. Better evaluation of classification techniques for images with larger coverage from high-resolution satellites can be obtained.

A spatial fuzzy clustering algorithm that exploits the spatial contextual information in image data is introduced in [5]. Spatial fuzzy c-mean clustering algorithm can perform unsupervised clustering and classification of image data using both the feature space information and the spatial contextual information. The key to the algorithm is a new dissimilarity index that takes into account the influence of the neighboring pixels on the centre pixel in a 3 x 3 window. The new index is adaptive to the image content within the window. If the window is in a non homogeneous region, the influence of the neighboring pixels on the centre pixel is suppressed; otherwise, the centre pixel is smoothed by its neighboring pixels during the computation of the membership values and the cluster centroids. The algorithm seems good at resolving classification ambiguity for data in the overlapping region of two clusters. **A** cluster merging scheme that merges clusters which are close together and with significant overlap is given. The merging scheme allows the algorithm to reach an 'optimal' partitioning of the data automatically. The new algorithm should be useful in applications such as multispectral image segmentation and image texture segmentation here spatial contextual information is important.

Experimental results with synthetic and real images indicate that the proposed algorithm is more tolerant to noise, better at resolving classification ambiguity and coping with different cluster shape and size than the conventional fuzzy c-means algorithm.

Satellite image time series (SITS) analysis is an important domain with various applications in land study. In the coming years, both high temporal and high spatial resolution SITS will become available [7]. When dealing with high spatial resolution images, object-based approaches are generally used in order to exploit the spatial relationships of the data. However, these approaches require a segmentation step to provide contextual information about the pixels. Even if the segmentation of single images is widely studied, its generalization to series of images remains an open-issue. Article [7] aims at providing both temporal and spatial analysis of SITS.

The approach starts in segmenting the image in to regions, for each region features values are extracted like spectral, geometrical, topological, etc once a region is characterized by a (multidimensional) feature value; it is then possible to affect this value to all the pixels composing the region. Now we have pixel value and region associated value which are used to construct vector image and used in classification.

To improve the analyzing process by using the spatial relationships of the data, object-based methods have been recently proposed (Blaschke, 2010). In a first step, the images are segmented/ partitioned into sets of connected regions. Then for each region, geometric features (Carleer and Wolff, 2006) (e.g., area, elongation, smoothness) or even contextual ones (Gaetano et al., 2009; Bruzzone and Carlin, 2006; Kurtz et al., 2010) (e.g., spatial context, multi-scale/multi-resolution attributes) are computed in order tocharacterize the regions. Finally, the regions are classified using these features (Herold et al., 2003) Object-based methods have shown promising results in the context of single-image analysis.

In the tasks such as clustering or nearest-neighbor queries, expected distance is often used as a distance measurement among uncertain data objects. Traditional database systems store uncertain objects using their expected (average) location in the data space [8]. Recent research work calculates the expected distance by calculating the weighted average of the pair-wise distances among samples of two uncertain objects. However the pair-wise distance calculations take much longer time than the former method. In [8] proposes an efficient method Approximation by Single Gaussian (ASG) to calculate the expected distance by a function of the means and variances of samples of uncertain objects. Theoretical and experimental studies show that ASG has both advantages of the latter method's high accuracy and the former method's fast execution time. ASG plays an important role in reducing computational costs significantly in query processing and various data mining tasks such as clustering and outlier detection.

Analytical solutions of special cases (uniform and Gaussian distributions) and five approximation methods for general cases (arbitrary distributions) are proposed in [8]. It is shown theoretically and experimentally that ASG, in a very short execution time, can obtain results of very high accuracy (compared with other existing methods that use sampling). This strongly suggests that ASG can replace the existing calculation method used in recent research work for answering queries as well as data mining applications on uncertain data.

Three approaches to utilizing object-level spatial contextual information for semantic image analysis are presented and comparatively evaluated[9].All techniques, namely a Genetic Algorithm (GA), a Binary Integer Programming (BIP) and an Energy-Based Model (EBM), are applied in order to estimate an optimal semantic image interpretation, after an initial set of region classification results is computed using solely visual features.

In this paper, three approaches to spatial context exploitation that make use of fuzzy directional relations were presented and comparatively evaluated. The selected techniques include a GA, a BIP and an EBM, and each of them is applied after an initial set of region classification results based solely on visual features is computed. Extensive experiments on six datasets of varying complexity demonstrated the influence of a series of factors on their region- concept association performance.

GA is employed for deciding on the optimal semantic image interpretation ,through the tuning of the GA's parameters (like selecting a sufficiently large number of chromosomes in every population, choosing an appropriate selection operator, selecting a suitable crossover operator, and adjusting the probabilities of mutation and crossover) the employed GA is adapted to the problem of spatial context exploitation and it is shown experimentally that it is capable of reaching a solution close to the optimal one (if not the global maximum).

Binary integer programming BIPs are a specific type of linear programs, which allow the definition of only binary integer variables the task of computing an optimal region-concept association is expressed in the form of a BIP, which can be solved efficiently and takes into account the initial classification results as well as the acquired spatial constraints. In order to represent the problem of concern, i.e. spatial context exploitation, as a binary integer program, a set of linear constraints for each spatial relation need to be defined [50].

The EBM is represented with a graph, where each node corresponds to a region of the examined image. Dependencies among regions are denoted by edges. At the evaluation stage, the EBM receives as input the visual analysis results, as well as the spatial relations then, it assigns a particular concept to every region, ensuring that its overall energy value E is minimized.

The main outcomes of the work [9] regarding the exploitation of spatial context in semantic image analysis are summarized as follows: Spatial context is efficient in improving the initial (i.e. based solely on visual features) region-concept association results; exhibiting an overall increase of up to 9.25% in the current evaluation framework. The highest on average performance is achieved when complex spatial constraints are acquired and their weight against the visual and co-occurrence information is efficiently adjusted (this is better accomplished by the BN-based approach followed by the GA, rather than the global weights of the EBM or the product operator of the BIP).

Aim of [9] is the in-depth investigation of the advantages of each technique and the gain of a better insight on the use of spatial context. For this purpose, an appropriate evaluation framework, which includes several different combinations of low-level features and classification algorithms, is developed. Extensive experiments on six datasets of varying problem complexity have been conducted for investigating the influence of typical factors (such as the utilized visual features, the employed classifier, and the number of supported concepts) on the performance of each spatial context technique, while a detailed analysis of the obtained results is also given

Learning from unlabeled images that contain various objects that change in pose, scale, and degree of occlusion is a challenging task in computer vision [10]. Shared structures embody the consistence and coherence of features that repeatedly co occurs at an object class. They can be used as discriminative information to separate the various objects contained in unlabeled images.

Method is able to separate the original object from the distracting objects. Steps to maximize the likelihood for shared structure learning: (1) feature extraction; (2) clustering; (3) exploring consistent pair wise relationships; (4) combining pair wise relationships into high order structures, Histogram of Oriented Gradient (HOG) descriptor [13] is used to extract image features at multiple scales. HOG descriptors describe local object appearance and shape within an image using the distribution of intensity gradients or edge directions.

The image is divided in two small regions called cell, for each cell histogram of gradient directions or edge orientations for the pixels is calculated. Combination of these histograms then represents the descriptor. Since the Histogram of Oriented Gradients descriptor operates on localized cells, the method upholds invariance to geometric and photometric transformations such changes would only appear in larger spatial regions.

In the first stage of clustering features are grouped in different clusters, and each cluster is assigned a distinct label. In the Second stage of clustering is then performed on a subset of each of these clusters. Each subset contains the features extracted in the same image.

The neighboring features grouped together by the second stage of clustering are treated as a single image segment. Spatial relationships are defined in terms of the distance and the direction between image segments. A circular histogram is used to code distance and direction discretely into bins.

[10] Propose a maximum likelihood algorithm for unsupervised shared structure learning. A four-step learning process is used to realize the algorithm. Finally, we provide quantitative results of our methods on Caltech dataset. If the shared structures that correspond to the same classes are combined together, object location or object categorization will be more accurate. And more primitive features such as edges might improve robustness to background clutter and shape ambiguity. Our future work will continue in the above directions.

3. Conclusion

The Spatial mining techniques explored is useful for particular application and on particular or specific images, mining techniques aims not only to reduce the time of searching but also to be more accurate in retrieving specific image, analyzing, predicting. These techniques can be effectively used by combining different algorithm and concepts. Main goal of any mining techniques is not only just mining it should also be efficient and effective. Mining technique efficiency is measured in terms of its performance – Reduction time in transforming the image to data set .Reduction in the size of the transformed image data and the time to mine the bulk data. Mining technique effectiveness is the percent age of accuracy in identifying, retrieving, searching images.

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