Research Article Impact Factor: 0.621 ISSN: 2319-507X
MS Makesar, IJPRET, 2014; Volume 2 (8): 227-234 IJPRET

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

ANALYSIS OF IMAGE MINNING TECHNIQUES

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Accepted Date: 15/02/2014 ; Published Date: 01/04/2014

Abstract: This paper presents a survey on the problems and solutions in Multimedia Data Mining In recent years, multimedia data like pictures, audio, videos, text, graphics, animations, and other multimodal sensory data have grown at a phenomenal rate and are almost ubiquitous. As a result, not only the methods and tools to organize, manage, and search such data have gained widespread attention but the methods and tools to discover hidden knowledge from such data have become extremely important Data mining refers to the process of finding interesting patterns in data that are not ordinarily accessible by basic queries and associated results with the objective of using discovered patterns to improve decision making.

Keywords: Preprocessing, feature extraction, Transformation, Image mining, Classification, Association, Clustering

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Access Online On:

www.ijpret.com

How to Cite This Article:

MS Makesar, IJPRET, 2014; Volume 2 (8): 227-234

PAPER-QR CODE

INTRODUCTION

Advances in data acquisition and storage technology have led to the growth of very large image databases. Analyzing this huge amount of image data to discover useful knowledge is a challenging problem. This challenge has opened the opportunity for research in Image mining. Image mining can be defined as the process of finding interesting patterns from large image databases. The motivation for doing Image mining is to use the discovered patterns to improve decision making. Image mining has therefore attracted significant research efforts in developing methods and tools to organize, manage, search and perform domain specific tasks for data from domains such as surveillance, meetings, broadcast news, sports, archives, movies, medical data. This paper presents , approached from the following angles: feature extraction, transformation and representation techniques, data mining techniques, and current data mining systems in various application domains. We discuss main aspects of feature extraction, transformation and representation techniques. These aspects are: level of feature extraction, feature fusion, features synchronization, feature correlation discovery and accurate representation of image data.

2. Image mining

Image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images. Image mining is more than just an extension of data mining to image domain. The fundamental challenge in image mining is to determine how low-level pixel representation, contained in a raw image or image sequence, can be efficiently and effectively processed to identify high-level spatial objects and relationships. For example, many photographs of various painting have been captured and stored as digital images. These images, once mined, may reveal interesting patterns that could shed some light on the painters and artistic genres. Clearly, image mining is different from low-level computer vision and image processing techniques. The focus of image mining is in the extraction of patterns from a *large collection* of images, whereas the focus of computer vision and image processing techniques is in understanding and/or extracting specific features from a *single* image. While there seems to be some overlap between image mining and content-based retrieval (since both deals with large collection of images), image mining goes beyond the problem of retrieving relevant images. In image mining, the goal is the discovery of image patterns that are significant in a given collection of images and the related alphanumeric data .

1.1 Preprocessing

In image data, the spatial segmentation can be done at region and/or edge level based on the requirements of the application. It can be automatic or with manual intervention and should be

approximate enough to yield features that can reasonably capture the image content. In many image mining applications, therefore, the segmentation step often involves simple blob extraction or image partitioning into fixed size rectangular blocks . In some of the image mining applications like medical image mining noise from the image is removed. For example, the cropping operation can be performed to remove the background, and image enhancement can be done to increase the dynamic range of chosen features so that they can be detected easily .

1.2 Feature extraction and transformation

Color, edges, shape, and texture are the common image attributes that are used to extract features for mining. Feature extraction based on these attributes may be performed at the global or local level.

Color histogram of an image may be obtained at a global level or several localized histograms may be used as features to characterize the spatial distribution of color in an image. Here one can choose RGB or HSV any suitable color space for feature extraction. Apart from the choice of color space, histograms are sensitive to the number of bins and position of bin boundaries. They also do not include any spatial information of colors. Swain and Ballard proposed color histogram intersection for matching purposes. Color moments have been proposed in as a more compact representation. Color sets as an approximation of the color histogram proposed in are also an improvement over the global histogram, as it provides regional color information. The shape of a segmented region may be represented as a feature vector of Fourier descriptors to capture global shape property of the segmented region or a shape could be described in terms of salient points or segments to provide localized descriptions.

There are obvious trade-offs between global and local descriptors. Global descriptors are generally easy to compute, provide a compact representation, and are less prone to segmentation errors. However, such descriptors may fail to uncover subtle patterns or changes in shape because global descriptors tend to integrate the underlying information. Local descriptors, on the other hand, tend to generate Multimed Tools Appl (2011) 51:35–76 43 more elaborate representation and can yield useful results even when part of the underlying attribute, for example, the shape of a region is occluded, is missing.

2.1. Image mining techniques

In image mining, the patterns types are very diverse. It could be classification patterns, description patterns, correlation patterns, temporal patterns, and spatial patterns.

2.1.1 Classification

Intelligently classifying image by content is an important way to mine valuable information from large image collection. There are two major types of classifiers, the parametric classifier and non-parametric classifier. MM-Classifier, the classification module embedded in the MultiMedia Miner developed by , classifies multimedia data, including images, based on some provided class labels. Wang and Li propose IBCOW (Image-based Classification of Objectionable Websites) to classify whether a website is objectionable or benign based on image content. Vailaya et al. uses binary Bayesian classifier to attempt to perform hierarchical classification of vacation images into indoor and outdoor categories. An unsupervised retraining technique for a maximum likelihood (ML) classifier is presented to allow the existing statistical parameter to be updated whenever a new image lacking the corresponding training set has to be analyzed. Gaussian mixture model (GMM) approach uses GMMs to approximate the class distributions of image data .

The major advantage of the GMM-based approach is that prior knowledge can be incorporated for learning more reliable concept models. Due to the diversity and richness of image contents, GMM models may contain hundreds of parameters in a

high-dimensional feature space, and thus large amount of labeled images are needed to achieve reliable concept learning. The support vector machines (SVM) based approach uses SVMs to maximize the margins between the positive images and the negative images . The SVM-based approach is known by its smaller generalization error rate in high-dimensional feature space. However, searching the optimal model parameters (e.g., SVM parameters) is computationally expensive, and its performance is very sensitive to the adequate choices of kernel functions. Fan et al. has mined multilevel image semantics using salient objects and concept ontology for hierarchical classification for images. Previous works on hierarchical image classification are , where Media Net has been developed to represent the contextual relationships between image/video concepts and achieve hierarchical concept organization.

For web image mining, the problem of image classification is formulated as the calculation of the distance measure between training manifold (learned from training images) and test manifold (learned from test images). Classifying images with complex scenes is still a challenging task owing to their variability, ambiguity, and the wide range of illumination and scale conditions that may apply. Such image classification methods are extended for image annotation with the goal of obtaining greater semantic understanding of images. Automatic image annotation systems take advantage of annotated images to link the visual and textual modalities by using Multimed Tools data mining techniques.

2.1.2 Clustering

In unsupervised classification (or image clustering), the problem is to group a given collection of unlabeled images into meaningful clusters according to the image content without a priori knowledge . Chang et al. uses clustering technique in an attempt to detect unauthorized image copying on the World Wide Web. Jain et al. uses clustering in a preprocessing stage to identify pattern classes for subsequent supervised classification. They also described a partition based clustering algorithm and manual labeling technique to identify classes of a human head obtained at five different image channels (a five dimensional feature vector).

In image segmentation is treated as graph partitioning problem and solved using minimum spanning tree based clustering algorithm. Automated image mining is necessary in several applications. In the problem to apply appropriate clustering and classification to different types of images, and to decide on such processing automatically is discussed.

2.1.3 Association

Ordonez and Omiecinski present an image mining algorithm using blob needed to perform the mining of associations within the context of images. A prototype has been developed called Multimedia Miner where one of its major modules is called MM-Associator. In another application association rule mining used to discover associations between structures and functions of human brain . In association rule mining technique is used to classify the CT scan brain images into three categories namely normal, benign and malign. In association rules relating low-level image features to high-level knowledge about the images are discovered to select the most relevant features for application in medical domain.

2.1.4 Visualization

Fan et al. has proposed new algorithm to achieve hyperbolic visualization of large scale concept ontology and images resulting from hierarchical image classification.

Zaiane et al. uses 3-dimensional visualization to explicitly display the associations. Though we have seen the diverse applications of image mining in literature, the effectiveness of image data mining can be appreciated only when we associate semantic information with images like annotations etc. As can be seen later in the multimodal data mining section, images with text annotations can be very effective for learning semantic level information.

Task	Approach	Issue
Preprocessing	Pixel, region and grid level	Global vs. local level features
Feature Extraction and Transformation	Colorhistograms, color moments, color sets, edges, Shape descriptors	Sensitive to the parameters bin boundaries, selection of feature vectors.
Image Classification	GMM,SVM,Bayesian classifier to classify image	Large training data needed for GMM,SVM kernel functions etc.
Image Clustering	K-means in preprocessing Stage to identify patterns.	Unknown numbers of clusters.
Image association	A-priori based association between structures and functions.	Scalability issue in terms of candidate .patterns generated

DISCUSSION

Some of the common issues of image mining are summarized as shown in the Table. Image mining applications started with use of data mining methods on low-level image features. Later on, the limitation of the approach was realized. Firstly, this approach is normally used to classify or cluster only a small number of image.

The modeling of images by a semantic intermediate representation was next proposed in order to reduce the gap between low-level and high-level image processing. One way is to detect objects in an image using object classifiers, and then the image is represented by the occurrence of these semantic objects. Another way is to represent semantics of an image by visual word distribution where intermediate properties are extracted from local descriptors. The intermediate semantic modeling provides a potentially larger amount of information that must be exploited to achieve a higher performance for image mining.

However, it needs to tackle the problem of uncertainty/inaccuracy involved in a local/ region processing and object recognition. Earlier image mining was limited to the specific set of images as personal photo album or CT scan image as dataset, whereas the recent approaches are considering web scale images as dataset. Thus, recent research is focuses on developing image mining frameworks that can handle different types of images at large scale automatically.

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