IMAGE CLASSIFICATION USING CONTENT BASED IMAGE RETRIEVAL SYSTEM

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Abstract: Image Classification in Content Based Image Retrieval deals with classifying all pixels in a digital image into one of several classes. For example in an agricultural scene, each pixel could be assigned the class wheat, rice or barley. The classified images are extremely useful for searching and browsing through large collection of images.

Two main approaches used in image classification are supervised classification where the classes are specified a priori by an analyst and unsupervised classification where the pixels are automatically clustered into a set of prototype classes where the analyst merely specifies the number of desired categories.

Our approach to image classification is to segment the image into regions using low level features like color, texture and position in the training phase. After segmenting the image into regions the regions are assigned labels by the analyst. In the testing phase given a new image the image is segmented into regions and the regions are compared with the regions in the database for similar matches and are classified into one of the classes. Segmentation of the images is done using Maximum Likelihood Classifier using color, texture and position features.

Keywords: Supervised Classification, Unsupervised Classification, Segmentation, Content Based Image Retrieval.

1. INTRODUCTION

The proliferation of the world-wide web has given easy access to growing volume of visual data. Unfortunately, this data in almost all cases is both scattered and unorganized, making search and retrieval of information difficult. Large digital libraries built by collecting resources from different locations, can make searching relatively easier. Users are not only interested in searching for specific images or video shots, but would also like to browse and navigate through the image corpus. Such requirements have created great demands for effective and flexible systems to manage digital images and videos. Almost all the content based image retrieval systems utilise low-level image features such as color, texture, shape, motion, etc., for image indexing and retrieval. This is partly because low-level features (e.g., color histograms, texture patterns) can be computed automatically and efficiently. The semantics of images, with which users prefer most of their interaction, are seldom captured by low-level features. On the other hand, there is no effective method yet to automatically generate good semantic features of an image. One common compromise is to obtain some semantic information through manual annotations. As visual data contains rich information, and the manual annotation process is quite subjective and ambiguous, it is very difficult to capture the content of an image using words, not to mention the tedium work involved in such a process. Image classification is the task of classifying images into semantic categories based on the available training data. This categorization of images into classes can be helpful both in semantic organization of digital libraries and in obtaining automatic annotations of images. These issues limit the applicability of object based and knowledge based approaches.

A common approach to image classification involves addressing the following three issues:
1. Image Features: How to represent the image.
2. Organization of feature data: How to organize the data, and
3. Classifier: How to classify the data. Acquiring good image features and carefully modeling the feature data are vital steps in this approach.

As mentioned before, image classification can lead to a semantic organization of a digital database.

This type of organization has multifold advantages:
1. Easy browsing and navigation through the database.
2. Efficient retrieval.
3. Easy representation of the database.

The primary objective of this paper is to classify an image into one of the predefined classes. This is subdivided into following objectives:
1. Extracting low level features for the images.
2. Segmenting the images into regions using low level features.
3. Describing or labeling the images in the database after segmentation.
4. Classifying the testing set images semantically with the help of training feature set.

2. CBIR

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content based visual information retrieval (CBVIR) is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. “Content based” means that the search makes use of the contents of the images themselves, rather than relying on human input metadata such as captions or keywords. There is growing interest in CBIR because of the limitations inherent in metadata-based systems. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically. It is also possible to miss images that use different synonyms in their descriptions. CBIR eliminates this problem by searching the content in the image rather than the label used to describe the image. This type of open-ended task is very difficult for computers to perform because the pictures are not always taken in the same pose. Current CBIR systems therefore generally make use of lower-level features like texture, color, and shape, although some systems take advantage of very common higher-level features like faces. Different implementations of CBIR make use of different types of user queries.

1. With query by example, the user searches with a query image (supplied by the user or chosen from a random set), and the CBIR system finds images similar to it based on various low level criteria.
2. With query by sketch, the user draws a rough approximation of the image they are looking for, for example with blobs of color, and the software locates images whose layout matches the sketch.
3. Other methods include specifying the proportions of colors desired (e.g. “80% red, 20% blue”) and searching for images that contain an object given in a query image. CBIR systems can also make use of relevance feedback, where the user progressively refines the search results by marking images in the results as “relevant”, “not relevant”, or “neutral” to the search query, then repeating the search with the new information.

A content based image retrieval system is shown in Fig. 1 whose basic functionalities are:
1. For each image in the database, extract low level features from the image and store them in the feature database. This is an offline computation and is done once for the whole database.
2. Given query image, extract features for the query image and compare these features with the features in the database with a similarity measure.
3. Display results and take relevance feedback from the user and retrieve a new set of images.
3. IMAGE CLASSIFICATION

Classification is the process of sorting pixels into a finite number of individual classes or categories, based on their data file values. If a pixel satisfies a certain set of criteria then the pixel is assigned to the class corresponding to those criteria. An important part of image analysis is identifying groups of pixels that have similar characteristics and to determine the various classes represented by these groups. This form of analysis is known as classification.

There are two ways to classify pixels into different categories: Supervised and unsupervised. Supervised classification is more closely controlled by the analyst than unsupervised classification.

Classification will be made according to the following procedures as shown in Fig. 2.

Training data should be sampled in order to determine appropriate decision rules. Classification technique such as supervised or unsupervised learning is selected on the basis of the training data sets.

Step 4: Choosing a classification scheme

A proper decision rule is taken in choosing the classification scheme.

Step 5: Classification

Depending up on the decision rule, all pixels are classified with a classification technique.

Step 6: Verification of Results

The classified results are checked and verified for their accuracy and reliability.

Types of Classification

There are two types of classification schemes, unsupervised and supervised classification.

Supervised Classification

Supervised classification requires the user to identify the cover types of interest. Samples of pixels are then selected based on available ground truth information to represent each cover type. These samples are called training areas. The brightness values in the input image bands are analyzed to generate a spectral signature for each cover type. All pixels in the image are then compared to the spectral signatures of each cover and assigned to the cover class with which the pixel has the highest degree of similarity.

Typically supervised classification involves three steps:

1. The training stage, wherein the multi-spectral parameters are extracted for various classes from the training sites identified in the image.
2. The classification stage, wherein, each pixel is assigned to a class to which it most probably belongs, and
3. The output stage-the presentation of the data is in the form of maps, tables, graph, etc.

However this is common for unsupervised classification. Figure 3 shows the flow chart of the supervised classification scheme.

Figure 1: Content Base Retrieval System

Figure 2: Procedure for Classification

Step 1: Definition of Classification

Classes Depending on the objective and the characteristics of the image data, the classification classes should be clearly defined.

Step 2: Selection of Features

Features to discriminate between the classes such as color, texture etc., should be selected.

Step 3: Sampling of Training Data
Training Stage

The first step is to locate in the image, representative areas of each class. These areas, called training sites, are selected based on ground surveys, studying aerial photographs, etc. The site chosen should be homogeneous and a typical representation of the class. In addition, the sample size should be large enough to reliably estimate the statistical properties of the class.

Clustering is done by applying suitable algorithms on the bases of spectral signature, generating ‘spectral classes’. By ground verification (or verifying with other maps, etc.), each spectral class is assigned to a class on the ground. There are a number of statistical techniques for clustering. To carry out clustering, we should first define a measure of similarity between patterns and then we partition a set of patterns into clusters. One criteria for similarity measure is the distance between the data points in the feature space. Similar objects are expected to be ‘closer’ than the dissimilar object. The algorithm starts with an arbitrary cluster centers and the distances of each pixel from the cluster center are computed.

Each point is assigned to the nearest cluster center. Then a new mean value of the clusters are computed and the procedure is continued until there is no change in the pixel assignments from one iteration to the next. A flow chart of basic clustering algorithm is given in Fig. 4.

Unsupervised Classification

In supervised classification, the essential requirement is a set of training patterns, whose class membership is know. If such information is not available, unsupervised classification technique is adopted. Unsupervised classification is based on the fact that similar classes cluster in the feature space. Classification of an image involves three steps (see Fig. 5):

1. Extract color, texture, and position features for an image.
2. Group pixels into regions by modeling the distribution of pixel features with a mixture of Gaussians using Expectation-Maximization (EM).
3. Describe regions using a label in the feature database.
Feature Extraction

Before an image can be segmented, it must be transformed into a set of feature maps that permit similarity and surface continuity to be defined. The most commonly used features are color, texture, and position. Since the objective of segmentation is to achieve image regions that are meaningful to humans, the feature space should also be perceptually uniform. Furthermore, after feature extraction, the features must be integrated to form a single feature vector. This requires decisions about how the features should be combined and what to do if they contradict each other.

Color

Color has been the most effective feature and almost all systems employ colors. Although most of the images are in the RGB (Red, Green, Blue) color space this space is only rarely used for indexing and querying as it does not correspond well to the human color perception. It only seems reasonable to be used for images taken under exactly the same conditions each time such as trademark images.

Texture

Texture features of images refer to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. An image’s texture content provides information of image properties such as smoothness, coarseness, and regularity which is useful in a CBIR system.

Position

Including the position ((x, y) co-ordinates of the pixel in the image) generally decreases over segmentation and leads to smoother regions. Large, uniform background areas in the image are sometimes arbitrarily split into two pieces due to the use of position as a feature. On the whole however including position yields better segmentation results than excluding it.

Image Segmentation

Definition

The objective of segmentation is to partition an image into regions

\[
\text{SEGMENT (Input Image } I) \\
1. \text{ foreach (subspace } s \in S) \\
2. \text{ foreach (pixel } i \in I) \\
3. \text{ Compute quality } Q_s(i) \\
4. \text{ Compute clustering } C_s(I) \\
5. \text{ Compute labeling } L(I) \\
6. \text{ foreach (pixel } i \in I) \\
7. \quad C_f(i) = C_{L(i)}(i) \\
8. \text{ return } C_f \text{ as final segmentation}
\]

Region Labeling

Once an image has been segmented into regions, each blob in the image of the training set is labeled by the analyst by examining the feature set of the blob. The label is assigned next to the 17-D feature set of the blob in the feature database.

4. IMAGE RETRIEVAL BY QUERYING

In the past few years, a variety of image retrieval systems have become available. Most of these systems operate in a similar way the user performs a query by choosing an image which is somewhat similar to the desired image.Upon seeing the query results, the user may submit a new query based on the original image or one of the returned images. In a few systems, the user may also label the retrieved images as good or bad matches in order to provide more information to the retrieval algorithm this is called relevance feedback. Two major shortcomings of such interfaces are a lack of user control and the absence of information about the computer's view of the image. Unlike with text searches, in which the user can see the features in a document none of the current image retrieval systems allows the user to see exactly what the system is looking for in response to a query. Without knowing that the input image was not properly processed, the user can only wonder what went wrong. In order to help the user formulate effective queries and understand their results, as well as to minimize
disappointment due to overly optimistic expectations of the system, we believe the system should display its representation of the submitted and returned images and should allow the user to specify which aspects of that representation are relevant to the query.

5. RESULTS

Example: Top 12 images Retrieved for Query by label ‘Normal Vegetation (Red)’ which is to the North-East in Image.

The above shown figures are the results.

Here we have given the query image and the related or similar images have been retrieved using color texture and position features.

6. CONCLUSIONS

In this paper we presented an approach to classify image regions based on their semantics. The classification scheme employed here is supervised classification, where we have training phase classification phase and testing phase. In the training phase we extracted low level features such as color, texture and position for the training set images and then the pixels in the image are segmented using these low level features with Expectation-Maximization algorithm. The regions in the image are then labeled by the analyst. In the testing phase, the images are first segmented into blobs and then the blobs in each image are labeled using the feature set of the labels which are created in the training phase. A query by label CBIR system is developed where the user searches for the content in the image with label as the search criteria. We developed two systems where one uses low-level features of the classes which are calculated in the training stage for a similarity match in the testing set and another uses the semantics of the regions. The first type uses the segmentation system to segment the regions and store the low-level features. The second type of CBIR system makes use of both the segmentation system and classification system which assigns labels for the regions in the testing set. Both these systems have normal and advance search options. In the normal search the system finds the top matches for the class. The advanced search option allows the user to find images with a particular label at a particular position, or by the area occupied by the class in the image or by the texture pattern followed by the class in the image. Another form of CBIR system which uses semantics of the regions searches for matches with a particular class which are free of another class.

REFERENCES


