An Integrated Relevance Feedback Method for CBIR using Histogram Values, Texture Descriptor and Interactive Boosting

Dr. V. V. S. S. S. Balaram¹, Kranthi Kumar.K², Sunil Bhutada³

¹Professor & Head of IT, Sreenidhi Institute of Science and Technology, Yammampet, Ghatkesar, Hyderabad-501301, AP, INDIA
²Asst. Professor, Dept. of IT, Sreenidhi Institute of Science and Technology, Yammampet, Ghatkesar, Hyderabad-501301, AP, INDIA
³Associate Professor, Dept. of IT, Sreenidhi Institute of Science and Technology, Yammampet, Ghatkesar, Hyderabad-501301, AP, INDIA

Abstract

Image retrieval is an important topic in the field of pattern recognition and artificial intelligence. There are three categories of image retrieval methods: text-based, content-based and semantic-based. In CBIR, images are indexed by their visual content, such as color, texture, and shapes. Color and Texture information have been the primitive image descriptors in content based image retrieval systems. Many content-based image retrieval applications suffer from small sample set and high dimensionality problems. Relevance feedback is often used to alleviate those problems. In this paper, an integrating Relevance feedback for content based image retrieval based method is proposed for image mining based on analysis of color Histogram values and texture descriptor of an image and a novel interactive boosting framework to integrate user feedback into boosting scheme and bridge the gap between high-level semantic concept and low-level image features. For this purpose, three functions are used for texture descriptor analysis such as entropy, local range and standard deviation. To extract the color properties of an image, histogram values are used. The combination of the color and texture features of the image provides a robust feature set for image retrieval. Our method has advantage over the classic relevance feedback method in that the classifiers are trained to pay more attention to wrongfully predicted samples in user feedback through a reinforcement training process. It achieves more performance improvement from the relevance feedback than AdaBoost does because human judgment is accumulated iteratively to facilitate learning process.

Keywords — Relevance Feedback; Content-based image retrieval; Color Histogram; image texture; Image classification; Information retrieval; Pattern recognition; reinforcement training; Boosting;

1. INTRODUCTION

With the steady growth of computer power, rapidly declining cost of storage and ever-increasing access to the Internet, digital acquisition of information has become increasingly popular in recent years. Digital information is preferable to analog formats because of convenient sharing and distribution properties. This trend has motivated research in image databases, which were nearly ignored by traditional computer systems due to the enormous amount of data necessary to represent images and the difficulty of automatically analyzing images. Currently, storage is less of an issue since huge storage capacity is available at low cost. However, effective indexing and searching of large scale image databases remains as a challenge for computer systems. The Content Based Image Retrieval System (CBIR) is a system, which retrieves the images from an image collection where the retrieval is based on a query, which is specified by content and not by index or address. The query image is an image in which a user is interested and wants to find similar images from the image collection.

The Content Based Image Retrieval System (CBIR) is a system, which retrieves the images from an image collection where the retrieval is based on a query, which is specified by content and not by index or address. The query image is an image in which a user is interested and wants to find similar images from the image collection. The CBIR system retrieves relevant images from an image collection based on automatic derived features. The derived features include primitive features like texture, color, and shape. The features may also be logical features like identity of objects shown, abstract features like significance of some scene-depicted etc. There are many general-purpose image search engines. In the commercial domain, IBM QBIC is one of the earliest developed systems. Recently, additional systems have been developed at IBM T.J. Watson, VIRAGE, NEC AMORE, Bell Laboratory, Interpix (Yahoo), Excalibur, and Scour.net. In the academic domain, MIT Photobook is one of the earliest. Berkeley Blobworld, Columbia VisualSEEK and Web SEEK, CMU Informedia, UCSB
NeTra, UCSD, WBIIS are some of the recent systems. The proposed CBIR system can be extended at the other primitive feature vectors like, color and shape [1].

Color is a feature of the great majority of content based image retrieval system. However the robustness, effectiveness, and efficiency of its use in image indexing are still open issues. In image preprocessing, the features used to represent color information and the measures adopted to compute similarity between the features of two images are critically analyzed [2].

Feature extraction is very crucial step in image retrieval system to describe the image with minimum number of descriptors. The basic visual features of images include color and texture [3]. Research in content based image retrieval today is a lively field, expanding in breadth [4]. Representative features extracted from images are stored in feature database and used for object-based image retrieval [5].

Texture is another important property of images. Various texture representations have been investigated in pattern recognition and computer vision. Texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and Haar wavelet transform, characterize texture by the statistical distribution of the image intensity[1].

The mapping between high-level semantic concept and low-level image features is obtained by a learning process. The images are often preprocessed to extract statistical features, such as color, texture and shape. An image feature vector represents an image as data point in a high-dimensional space. Although Content-based image retrieval has been successfully applied in many fields, it still faces two major challenges.

Small Sample Set: In CBIR, a set of samples with categorical information are used to train a classifier. Because labeling the training samples requires human interference and could be computational expensive, the size of the training set is often very small. In that case the learning process tends to bias to the training set and over fitting could occur.

High Dimensionality: In many data analysis application, the observed data have very high dimensionality. Specifically the images in CBIR are represented by image feature vector whose dimensionality ranges from tens to hundreds in most cases. Traditional statistical approaches have difficulties in modeling data directly in such a high dimensional space.

Some techniques have been proposed to alleviate the two problems. Relevance Feedback [6] is one of the most widely used techniques to alleviate the small sample set problem. For the high dimensionality problem, it is almost a common practice to conduct dimension reduction to find a compact representation of data in a low dimensional space. Traditional techniques, such as Principal Component Analysis (PCA) [7] and Linear Discriminant Analysis (LDA) [8], have difficulties in finding optimal projection automatically when the data distribution cannot be modeled as Gaussian. Boosting could be used to alleviate that problem by combining a set of projection and corresponding classifiers in the projected space [9].

The main contributions of this paper are summarized as follows. Firstly, in this paper, we have provided brief survey of Relevance feedback and Boosting. Secondly, we have discussed briefly, about Color and Texture Feature Extraction. Finally, interactive boosting method. The paper is organized as follows. In section 2, we discuss the related work. In section 3, we discussed image retrieval is performed with the combined histogram value, texture descriptor & boosting. Finally, conclusion and future work is presented in section 4.

2. RELATED WORK

2.1 Relevance Feedback

Initially developed in documental retrieval [10], Relevance Feedback was transformed and introduced into content-based multimedia retrieval, mainly CBIR. Interestingly, it appears to have attracted more attention in the image field than the text field – a variety of solutions have been proposed within a short period and it remains an active research topic. As we discussed, a challenge in content-based image retrieval is the semantic gap between the high-level semantics in a human mind and the low-level computed features (such as color, texture, and shape). Users seek semantic similarity (e.g., airplane and bird are very similar in terms of low level features such as shape), but the machine can only measure similarity by feature processing. The early work in Relevance Feedback focused on heuristic techniques, e.g., feature axis weighting in feature space and tree structured self-organizing map (TS-SOM). The intuition is to emphasize those features that best cluster the positive examples and separate the positive from the negative examples. The assumption of feature independence is rather artificial. Learning in Relevance Feedback has been used in a more systematic way in the framework of optimization, probabilistic models, learning with small samples, pattern
classification, active learning, concept learning, and genetic algorithms.

2.2 Boosting

Boosting algorithms are designed to construct a “strong” classifier from a “weak” learning algorithm, presenting the superior result given by a threshold linear combination of the weak classifier. A “weak” classifier has probability of misclassification that is slightly below 50%, while a “strong” one achieves much less error rate on test data. This idea was rooted in the framework of PAC learning, where it was theoretically proved. Kearns and Valiant raised the question on how to actually construct such as conversion in [11]. Schapire and Freund took over the idea and worked their way to the invention of AdaBoost [12]. The following couple of years see a great number of empirical work showcasing its ability to improve prediction accuracy. While a broad spectrum of application domains has gone ahead and benefited from boosting, researchers nevertheless have been trying to explain it, resulting in a rich set of satisfactory theory. Yet a complete picture is still out-of-reach.

AdaBoost is often regarded as the generic boosting algorithm, since it is the first practical algorithm that embodies the idea of boosting and has become extremely well-known over the years. Thus a description of the AdaBoost algorithm serves as the introduction to the boosting idea. In order to boost the weak learning algorithm, the data is reweighed (the relative importance of the training examples is changed) before running the weak learning algorithm at each iteration. In other words, AdaBoost maintains a distribution (set of weights) over the training examples and selects a weak classifier from the weak learning algorithm at each iteration. Training examples that were misclassified by the weak classifier at the current iteration then receive higher weights at the following iteration. The end result is a final combined classifier, each component is the weak classifier obtained at each iteration, and each component classifier is weighted according to how this classifier performed during each iteration. AdaBoost performs better than state-of-the-art classification algorithms in many experiments, and it does not seem to overfit. Theories trying to explain this include the margin theory [13] and the additive logistic regression [14]. These explanations have in turns given modifications or improvements over the original AdaBoost.

2.3 Color and Texture Feature Extraction

Images retrieval can be performed from the digital image database on the basis of colour, shape or texture. Among all these three features combination of texture and colour feature works very effectively in most situations. According to Figure 1 when a query image is submitted for image retrieval, its color and texture features are extracted and matching operation is performed between query image features and the image features stored in database, the results closes to the query image is then retrieved from the database.

2.3.1 Color Feature extraction

Color histograms are frequently used to compare images. Examples of their use in multimedia applications include scene break detection and querying a database of images. Color histograms are popular because they are trivial to compute, and tend to be robust against small changes in camera viewpoint [15]. In this paper gray level variations are used to compute the histogram of any image. For this purpose the color image is first converted into gray level image. Then the histogram values are computed for gray level variations. According to histogram values, images are extracted from the database.

2.3.2 Texture Feature extraction

Feature extraction is very crucial step in image retrieval system to describe the image with minimum number of descriptors [16]. Texture is an important property of many types of images. To extract the texture features, entropy, local range and standard deviation measures are used as performance parameters.

Texture = (Entropy + Standard deviation + local Range)

1. Entropy

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. The value of entropy can be calculated as:
2. **Standard Deviation**
   The standard deviation value can be calculated as:
   \[ S = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2} \]
   where, 
   \[ \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \]

3. **Local Range**
   \[ LC = (\text{maximum value of chosen pixel} - \text{minimum value of chosen pixel}) \]

2.3.3 **Interactive Boosting**
Motivated by the strength and success of Boosting and Relevance Feedback, we propose a framework called Interactive Boosting, which can integrate user relevance feedback in the loop of boosting to better bridge the gap between semantic concept and image features.

The process can be described in the following steps:

**Step 1:** Train weak classifiers on the original labelled data set and assign weights to classifiers based on their performance.

**Step 2:** Predict the labels of unlabelled data and present a subset of unlabeled data with their predicted labels to the user.

**Step 3:** User gives feedback on the retrieved data.

**Step 4:** Data obtained from user relevance feedback is added to construct a new labelled data set and removed from unlabeled data set.

**Step 5:** The labelled data are weighted according to their predicted label correctness.

**Step 6:** Go back to Step 1.

3. **IMAGE RETRIEVAL IS PERFORMED WITH THE COMBINED HISTOGRAM VALUE, TEXTURE DESCRIPTOR & BOOSTING (PROPOSED SYSTEM)**

Combined value of color, texture feature and boosting works very effectively in most situations. This paper uses histogram, entropy, standard deviation and local range.

Image Retrieval= Color feature + Texture Feature + Boosting

**Algorithm for Proposed Scheme**

**Step 1:** Load database in the Mat lab workspace.

**Step 2:** Resize the image for [128, 128].

**Step 3:** Convert image from RGB to Gray.

**Step 4:** Normalize the gray image for fixed mean.

**Step 5:** Generate the histogram of RGB.

**Step 6:** Find entropy, standard deviation and local range of Gray.

**Step 7:** Load into Interactive Learning framework (Boosting).

**Step 8:** Combine the image feature.

**Step 9:** Load the test image.

**Step 10:** Apply the procedure 2-8 to find combine feature of test image.

**Step 11:** Determine the normalized Euclidean distance of test image with stored image of database.

**Step 12:** Sort the normalized Euclidean distance values to perform indexing.

**Step 13:** Display the result on GUI.

According to Figure 3 when a query image is submitted for image retrieval, its color features are extracted and matching operation is performed between query image features and the image features stored in database then the results closes to the query image is retrieved from the database. First we load the database in the Matlab workspace after loading the database we resize the image for [128, 128] to get the similar size of images after that we Convert images from RGB to Gray texture and Generate histogram for color image. Then we normalize the gray image for fixed mean. After this we find the entropy, standard deviation and local range of each image. When a test image is loaded we apply the procedure 2-8 to find combine feature of test image after that we determine the normalized Euclidean distance between query image and database image with indexing. The closest values are displayed on GUI as result.
4. CONCLUSION AND FUTURE WORK

The paper proposed a method for image retrieval using histogram values and texture descriptor analysis of image and interactive boosting framework to integrate user feedback into boosting scheme and bridge the gap between high-level semantic concept and low-level image features. We first convert a true color image into a gray level image. We then developed a mechanism for image retrieval based on the color histogram values. After extraction of color feature, texture features are extracted with the help of entropy, local range and standard deviation of image. Interactive boosting framework to integrate relevance feedback into boosting scheme for content-based image retrieval. Compared to the traditional boosting scheme, the relevance feedback by putting human in the loop to facilitate learning process. It is clear that the framework can bridge the gap between high-level semantic concept and low-level image features better.

When a query image is submitted, its color and texture value is compared with the color and texture value of different images stored in database and then submitted to the boosting scheme.

We will continue this research work in the following direction: 1) accommodating active learning techniques in the relevance feedback; 2) using different techniques to implement the base classifiers and 3) evaluate the performance difference among different boosting schemes.

References

[1] Texture Based Image Indexing and Retrieval, N Ganeshwara Rao, Dr. V. Vijaya Kumar, V Venkata Krishna.


Dr. V V S S S Balaram is currently with Sreenidhi Institute of Science and Technology, Hyderabad, India, working as Professor and Head in the Department of Information Technology. He has 17 years of teaching experience. He did his M.Tech from Andhra University and Ph.D from Osmania University. His areas of interest include Network Security And Cryptography, Data warehousing and Mining, Operating Systems, Distributed Operating Systems and Computer Graphics. He has got many International Publications to his credit.

Kranthi Kumar K. is currently with Sreenidhi Institute of Science and Technology, Hyderabad, India, working as Asst. Professor in the department of Information Technology. He has 10 years of experience in Teaching. Graduated in B.Tech (CSE) from JNTU Hyderabad in 2003. Masters Degree in M.Tech (CSE), from JNT University, Anantapur, AP in 2007. He is pursuing his Ph.D in Computer Science & Engineering from JNT University, Hyderabad. His areas of Interests are Image Processing, Information Retrieval Systems, Database Management Systems, Distributed Databases, Computer Networks and etc.,

Sunil Bhutada Graduated in B.E.(CSE) from Amravathi University in 1993. He received Masters Degree in M.Tech.(Software Engineering), from JNT University, Hyderabad, in 2006. He worked as Software Engineer thereafter and later shifted to academics in 1998. He is currently attached with Sreenidhi Institute Of Science & Technology in Hyderabad as Associate Professor in IT department. Her areas of interest include Data Mining, Information Security, Information Retrieval System Presently he is pursuing Ph.D from Jawaharlal Nehru Technological University, Hyderabad, India, in the field of Data Mining.