Multi-SVM For Enhancing Image Search

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Abstract — Searching of relevant images from a large dataset for the given query image is a challenging task in computer vision systems. To overcome the problems such as time complexity and computational complexity a new methodology is proposed that will classify the whole dataset and also the given query image .By doing so we can reduce the similarity searching time and retrieval performance achieved by the classifier named Multi-SVM. Similarity measures are taken for query image against the whole database by using KNN. The images which are similar to the query image are retrieved from the database and displayed to the user. The images are categorized based on the extracted texture and color moment features. Finally compute precision and recall measures for CBIR performance analysis.

Index Terms — CBIR, TBIR,Multi-SVM,KNN

1.INTRODUCTION

WITH the ever-growing number of images on the Internet (such as in the online photo sharing Website the online photo forum, and soon), retrieving relevant images from a large collection of data- base images has become an important research topic. Over the past years, many image retrieval systems have been developed, such as text-based image retrieval (TBIR) [4], [13], [20], and content-based image retrieval [24], based on visual features to rerank the retrieved relevant images. After that, an image-based ranking of Web pages is generated, and the final search result is obtained by combining with the original text-based search result. Hsu et al. [13] presented a reranking method via the information bottleneck principle based on mutual information. In their work, they first clustered the initially retrieved images together with some irrelevant images by using a so-called sequential information bottleneck clustering method [27]. Then, a cluster probability is obtained for cluster ranking. Finally, KDE based on visual features is used to rerank the relevant images within each cluster. Several graph-based reranking methods [14], [15], have been also developed. The basic idea is to construct a graph representing the local similarity of visual features of images for reranking. However, the similarity of low-level visual features among the unconstrained Web images may not reflect the high-level semantic concepts of Web images due to the semantic gap. Moreover, this reranking paradigm does not consider label information and can only achieve limited improvements.

To address this issue, relevance feedback (RF) methods [6], have been proposed to acquire the search intentions of the user for further improving the retrieval performance. However, they mentioned that the term feedback was not effective in the TBIR. For more comprehensive reviews of image retrieval, interested readers can refer to two surveys in [7] and [28].

To improve the retrieval performance, here introduce a new way of using SVMs to learn a n-class classification problem consists in choosing the maximum applied to the outputs of n SVMs solving a one per decomposition problem. In the training stage, the texture and color moment features were extracted for all the images in whole database and then they will be stored as a feature matrix. Then the feature matrix will be given to n-class SVM for classification. In testing stage the given query image is also classified in the same way as mentioned above. Similarity measures are taken for query image against the whole database. The images which are similar to the query image are retrieved from the database and displayed to the user.

2 . PROPOSED WORK

A. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features Transferring the input data into the set of features is called feature extraction. The features provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. If the extracted features are carefully chosen, it is expected that they will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Feature extraction is simplifying the amount of data required to describe a large set of data accurately. When performing analysis of hard data one of the major problems stems from the number of data's involved. Analysis with a large number of data's generally requires a large amount of memory and computation power or a classification algorithm which over fit's the training sample and generalizes poorly to new samples. Feature extraction can be used in the area of image processing which involves using algorithms to detect and isolate various desired portions or shapes (features) of a digitized image or video stream.

ISSN 2229-5518

Another important feature processing stage is feature selection.. However, when large and complicated feature sets are used to train on smaller training sets, classifiers can ‗over fit' the learned model, since it is likely that spurious patterns can be found that can accurately classify the training data, but are not relevant to unseen test data. Feature selection is partially up to the designer to select an appropriate feature set, but automatic methods can also be used. In selecting features, it is important to consider whether features will help in discriminating unseen data, and how complicated the interactions between the features are likely to be in order for them to be used in discrimination.

i.Extraction of Texture Feature

GLCM

- A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values.
- A co-occurrence matrix is a two-dimensional array, **P**, in which both the rows and the columns represent a set of possible image values.
- A GLCM **Pd**[i,j] is defined by first specifying a displacement vector **d**=(dx,dy) and counting all pairs of pixels alienated by **d** having gray levels i and j.

- The **GLCM** is defined by:

– $\mathbf{n_{ij}}$ is the number of occurrences of the pixel values **(i,j)** lying at distance **d** in the image.
– The co-occurrence matrix $\mathbf{P_d}$ has dimension **n× n**, where n is the number of gray levels in the image. For example, if **d**=(1,1)

$$\begin{bmatrix} 2 & 1 & 2 & 0 & 1 \\ 0 & 2 & 1 & 1 & 2 \\ 0 & 1 & 2 & 2 & 0 \\ 1 & 2 & 2 & 0 & 1 \\ 2 & 0 & 1 & 0 & 1 \end{bmatrix} \qquad P_d = \begin{array}{c|ccc} & 0 & 1 & 2 \\ \hline 0 & 0 & 2 & 2 \\ 1 & 2 & 1 & 2 \\ 2 & 2 & 3 & 2 \end{array}$$

there are 16 pairs of pixels in the image which satisfy this spatial separation. Since there are only three gray levels, **P[i,j]** is a **3×3** matrix.

Algorithm:

• Count all pairs of pixels in which the first pixel has a value ***i***, and its matching pair displaced from the first pixel by **d** has a value of ***j***.
• This count is entered in the $\mathbf{i^{th}}$ row and $\mathbf{j^{th}}$ column of the matrix $\mathbf{P_d[i,j]}$
• Note that $\mathbf{P_d[i,j]}$ is not symmetric, since the number of pairs of pixels having gray levels **[i,j]** does not necessarily equal the number of pixel pairs having gray levels **[j,i].**

From the co-occurrence matrix obtained, we have to extract the 12 different statistical features. Contrast,.Correlation,Cluster prominence,Cluster shade,Dissimilarity,Energy,Entropy etc..

Contrast:

Contrast is a measure of the local variations present in an image.

$$C(k, n) = \sum_i \sum_j (i-j)^k P_d[i, j]^n$$

Homogeneity:

A homogeneous image will result in a co-occurrence matrix with a combination of high and low P[i,j]'s

$$C_h = \sum_i \sum_j \frac{P_d[i, j]}{1 + |i - j|}$$

Entropy:

Entropy is a measure of information content. It measures the randomness of intensity distribution.

$$C_e = -\sum_i \sum_j P_d[i, j] \ln P_d[i, j]$$

Correlation:

Correlation is a measure of image linearity.

$$C_c = \frac{\sum_i \sum_j [ijP_d[i, j]] - \mu_i \mu_j}{\sigma_i \sigma_j}$$

$$\mu_i = \sum iP_d[i, j], \quad \sigma_i^2 = \sum i^2 P_d[i, j] - \mu_i^2$$

ii.Extraction of Color Feature

Color moments are used differentiate images based on their features of color., These moments provide a measurement for color similarity between images. These similarity values can be compared to the values of images indexed in a database for image retrieval. The moments are like mean, Standard Deviation, Skewness .

1.**Mean -** Mean can be understood as the average color value in the image.

$$E_i = \sum_{N}^{j=1} \frac{1}{N} P_{ij}$$

2.Standard Deviation - The standard deviation is the square root of the variance of the distribution.

$$\sigma_i = \sqrt{\left(\frac{1}{N} \sum_{N}^{j=1} (p_{ij} - E_i)^2\right)}$$

3.Skewness - Skewness can be understood as a measure of the degree of asymmetry in the distribution.

$$s_i = \sqrt[3]{\left(\frac{1}{N} \sum_{N}^{j=1} (p_{ij} - E_i)^3\right)}$$

iii. Shape Feature Extraction

Moment invariants have been frequently used as features for image processing. Moments can be used to provide characteristics of an object that uniquely symbolize its shape. Shape recognition is performed by classification in the multidimensional moment invariant feature space. For that many techniques have been developed that derive invariant features from moments for object recognition. These techniques are notable by their moment definition, such as the type of data broken and the method for deriving invariant values from the image moments. It was that first set out the mathematical foundation for two-dimensional moment invariants and established their applications to shape recognition. These moment invariant values are invariant with respect to conversion, size and revolution of the shape. Hu defines seven of these shape descriptor values computed from central moments through order three that are independent to object conversion scale and direction Translation invariance is achieved by computing moments that are normalized with respect to the centre of severity so that the centre of mass of the distribution is at the origin (central moments). Size invariant moments can be derived from arithmetical invariants but these can be shown to be the result of a simple size normalization. From the second and third order values of the normalized inner moments a set of seven invariant moments can be computed which are independent of rotation.

Traditionally, moment invariants are computed based on the data provided by both the shape boundary and its center region. The moments used to make the moment invariants are defined in the nonstop but for practical implementation they are computed in the discrete form. Given a function f(x,y), these regular moments are defined by:

$$M_{pq} = \int\int x^p y^q f(x,y)dxdy$$

M_{pq} is the two-dimensional moment of the function *f(x,y)*. The order of the moment is (p + q) where p and q are both ordinary numbers. For implementation in digital from this becomes:

$$M_{pq} = \sum_X \sum_Y x^p y^q f(x,y)$$

To normalize for change in the image plane, the image centroids are used to define the central moments. The co-ordinates of the centre of gravity of the image are calculated using equation and are given by:

$$\bar{x} = \frac{M_{10}}{M_{00}} \qquad \bar{y} = \frac{M_{01}}{M_{00}}$$

The central moments can be defined in their separate representation as:

$$\mu_{pq} = \sum_X \sum_Y (x-\bar{x})^p (y-\bar{y})^q$$

The moments are further normalized for the effects of change of scale using the following formula:

$$\eta_{pq} = \mu_{pq} / \mu_{00}{}^{\gamma}$$

Where the normalization factor:

$\gamma = (p + q / 2) + 1.$ From the normalized central moments a set of seven values can be intended and are defined by:

$$\phi_1 = \mu_{20} + \mu_{02}$$

$$\phi_2 = (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2$$

$$\phi_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2$$

$$\phi_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2$$

$$\begin{aligned}\phi_5 = {} & (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) \\ & + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)\end{aligned}$$

$$\begin{aligned}\phi_6 = {} & (\mu_{20} - \mu_{02})((\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) + \\ & 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})\end{aligned}$$

$$\begin{aligned}\phi_7 = {} & (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) \\ & - (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)\end{aligned}$$

$$\phi_I,\ 1 \le I \le 7,$$

These seven invariant moments, set out by Hu, were additionally shown to be independent of rotation. However they are computed over the shape boundary and its interior region.

B. Classification by n-class SVM

This defines a grouping of all the classes in two disjoint group of classes. This grouping is then used to train a SVM classifier in the decision tree root node using the samples of the first group as correct(+ve) examples and the samples of the second group as incorrect(-ve)examples. The classes from the first group are being assigned to the first (left) subtree, while the classes of the second group are being assigned to the (right) second subtree. The process continues recursively until there is only one class per group which defines a leaf in the decision tree.

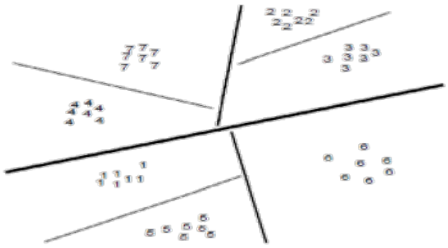


Fig 1.Block diagram for.Multi-svm clssifier

C. Relevant Image search by KNN within a category

Place items in class to which they are —bordering
Then determine distance between an item and a class.
Sorting the distances of most number of close images within a particular class and the nearest neighbor indexes are computed .

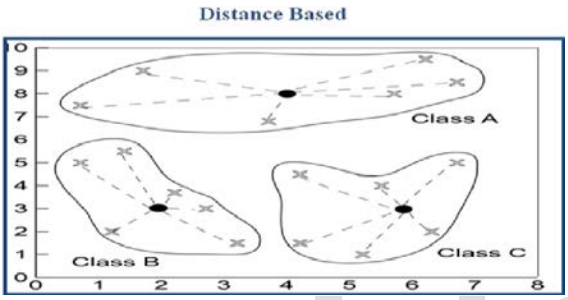


Fig 2. KNN search

D. Similarity Measurements and retrieval

After getting the relevant image ids from KNN search the corresponding database index will be computed by similarity feature matching. With the help of that database index values the relevant images are retrieved and displayed. The distance values are displayed and plotted as a bar graph.

E. Precision & Recall Analysis

CBIR performance is analyzed by computing the values of precision and recall.

Precision

precision is the fraction of retrieved images that are relevant

to the input image

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

Recall

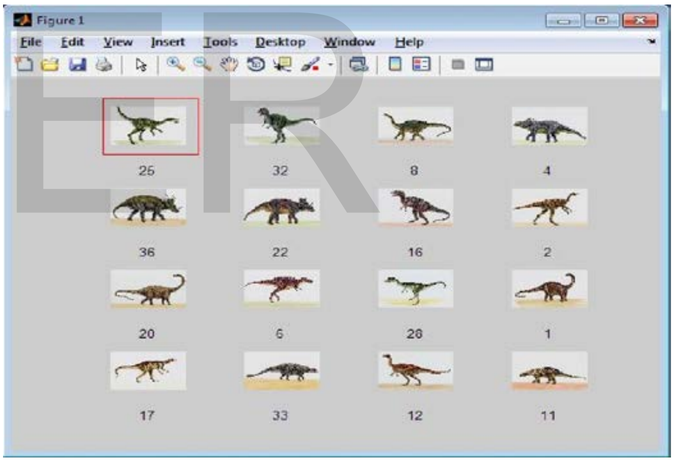
Recall is the fraction of the images that are relevant to the query that are successfully retrieved.

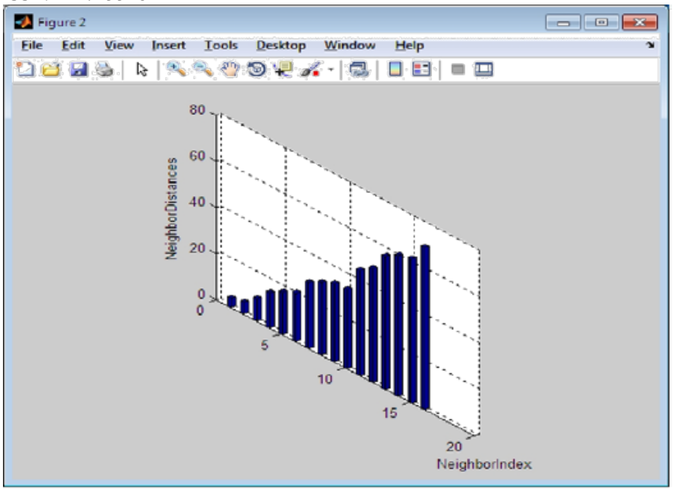
$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

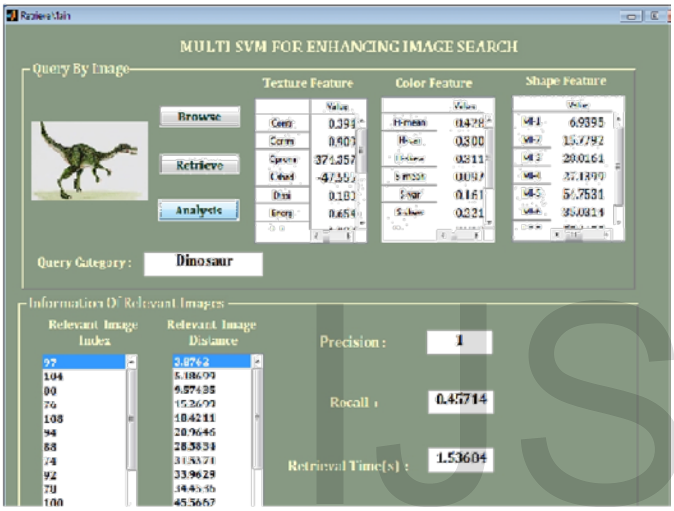
3.CONCLUSION

In this paper, we have proposed a multi-class svm for large scale CBIR. Given a query image , relevant images are to be retrieved after the feature extraction and classifying the whole data base as well as the given query image using multi -class svm. Then similarity measures are taken for query image against the whole database by using KNN. The images which are similar to the query image are retrieved from the database and displayed to the user. Finally precision and recall measures are computed for CBIR performance analysis.

4. RESULT







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