Content-based image retrieval system using neural network

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***Abstract*—Visual information retrieval has become a major research area due to increasing rate at which images are generated in many application. This paper addresses an important problems related to the content-based images retrieval. It concerns the vector representation of images and its proper use in image retrieval. Indeed, we propose a new model of content-based image retrieval allowing to integrate theories of neural network on a vector space model, where each low level query can be transformed into a score vector. Preliminary results obtained show that our proposed model is effective in a comparative study on two dataset Corel and Caltech-UCSD.**

I. Introduction

Content-based image retrieval (CBIR) is a new but widely adopted method for finding images from unannotated image databases. As the network and development of multimedia technologies are becoming more popular, users are not satisfied with the traditional information retrieval techniques. So nowadays the content based image retrieval (CBIR) are becoming a source of exact and fast retrieval. In recent years, a variety of techniques have been developed to improve the performance of CBIR.

The traditional solutions for CBIR uses the low-level features such as color, shape and texture [17]. By selecting proper feature caracteristics and distance metrics [18], the similarities between query and database images can be calculated and a ranking list is generated. The CBIR systems that use these techniques include QBIC system (Query By Image Content) of IBM [12], VisualSEEK system [10], the Frip system (Finding Areas in the Pictures) [1] and the RETIN system (Research and Interactive Tracking) [7] developed at the Cergy-Pontoise university, etc.

These systems allow the processing of images queries, but they do not make it possible to search for images based on their semantic content. This problem is called the semantic gap. A significant improvement of the performance of CBIR systems can be achieved by integrating the text-based techniques. These systems can use a manual annotation of images by text descriptors and then these descriptors are used to perform the image retrieval. These techniques requires a great effort by user for image annotation. Or the adaptation of textual retrieval techniques in image retrieval, such as the relevance feedback technique [30], the vectorisation technique [4] [5], Ostensive Model of developing information needs [31], etc.

Also there are the use of vector space model [4] [5] and the neural networks [11]. The vector space model is used in a general way when query and images are represented with feature vectors. The neural network is used in CBIR to organize images in classes [22], it is used to associate images in each class according to probabilities with which they are assigned.

Modern CBIR systems combine the visual and textual information [23] [24] to reduce the semantic gap that exists between objects and their visual representation [26].

The main attention in our research was addressed to present an image retrieval system based on neural network. The proposal is inside the classical semantic gap problem tackled with image data.

The main contribution of this paper is as follows. First, we study how to extract the features of query and how to calculate its score vector. Second, we propose a new retrieval model based on neural network. its construction takes into account the relationship between features and score vector of each images. With this model, the query result can be directly found through a matrix calculation. Unlike classic CBIR methods, the system retrieves the similar images for query from a large database through a similarity measure.

Finally, a few experiments on standard Corel and Caltech-UCSD collections have been conducted to evaluate our proposed retrieval model from different aspects. We compare our proposed retrieval model with the initial retrieval system and others retrieval systems. Our model can achieve significantly better performance that others model.

The remainder of this paper is organized as follows: in section 2 we review the related work. In Section 3, we describes in details our proposed model of image retrieval. In Section 4, we introduce the settings and the results of the experiments. A direct comparison is made to compare our model with other CBIR models. Finally, we conclude our work with a brief conclusion and future research directions in section 5.

II. Related Work

As the network and development of multimedia technologies are becoming more popular, users are not satisfied with the traditional information retrieval techniques. These techniques

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relied only on low-level features, also known as descriptors. In recent years, a variety of systems have been developed to improve the performance of CBIR, such as the system elaborate by lowe that proposes the scale-invariant feature transform (SIFT) to capture local image information SIFT [14]. The SIFT feature detects the salient regions in each image then it describes each local region with a 128 feature vector [3]. Its advantage is that both spatial and appearance information of each local region are recorded in correspondence with the spatial invariance changes in objects. As a result, an image can be viewed as a bag-of-feature-points (BOF) and any object within the image is a subset of the points. With each representation of the (BOF-points), image retrieval is carried out by comparing all feature points in query image to those from all images in the database. Therefore, image retrieval based on BOF-points representation is a solution to the problems with a large database images.

Others works are based on the RootSIFT [16] and the GIST [13] that learn the better visual descriptors (than SIFT) [20] or better metrics for descriptor comparison and quantization [8].

The texture is applied with Gabor filters method [2]. These values are gathered and classified via a neural network. The comparison between images is done through similarity calculation between their features [18]. Some studies were put forward to change their search spaces, such as color space variation descriptor [6]. Certain research works carried out the minimization of the search scope by calculating the closest neighbors designed to bring together the similar data in classes [19]. Thus, image retrieval is carried out by looking for a certain class.

There are also some papers that are based on combination of texture and color features. Jain et al. [27] provided an overview of the advantages of using an CBIR system by combining color histogram (CH) with K-Means strategy to propose the HDK method. Penatti et al. [28] presented a comparative study of color and texture descriptors by using (24 color descriptors and 28 texture descriptors, including both traditional and recently proposed ones). He made the evaluation based on two levels: A theoretical analysis in terms of algorithms complexities and an experimental comparison considering efficiency and effectiveness aspects. Singha et al. [29] presented the content based image retrieval using features like texture and color, called Wavelet Based Color Histogram Image Retrieval (WBCHIR). The texture and color features are extracted through wavelet transformation and color histogram and the combination of these features is robust to scaling and translation of objects in an image. He also demonstrated a promising and faster retrieval method on a WANG image database containing 1000 general-purpose color images.

The recent works on CBIR are based on the idea where an image is represented using a bag-of-visual-words (BoW), and images are ranked using term frequency inverse document frequency (tf-idf) computed efficiently via an inverted index [9].

The disadvantage of these systems is that the user does not always have an image meeting his actual need, which makes the use of such systems difficult. One of the solutions to this problem is the vectorization technique, which allows to find the relevant images with a query which are missed by an initial search. This process requires the selection of a set of images, known as reference. These references are selected randomly [21], or the first results of an initial search [5] or the centroids of the classes gathered by the K-means method [4].

All these retrieval systems are based on a query expressed by a set of low-level features. The extracted content influences indirectly the search result, as it is not an actual presentation of the image content. In order to avoid such problem, we introduce a new retrieval model to mend this problem.

In this paper, we propose a new retrieval model, which receives in the entry a query designed by a score vector, obtained through the application of an algorithm based on a neural network. This technique is a novel method, it is inspired from the textual retrieval systems (such as Mercure system [25]). Mercure is an information retrieval system based on a connexionnist approach and modeled by a multi-layered network. The network is composed of query layer (set of a query terms), a term layer (representing the indexing terms) and a document layer. Mercure includes the implementation of a retrieval process based on spreading activation forward and backward through the weighted links. Queries and documents can be used either as inputs or ouputs. The links between two layers are symmetric and theirs weigths are based on the tf-idf.

III. Proposed System

In this paper, we present a retrieval method based on neural network. This method aims to transform a content-based query process to a simple vector space model, which builds the connection between the query image and the result score directly via neural network architecture.

A. Content-based image retrieval process

The goal of content based image retrieval is to retrieve images that are visually similar to a query image. Three functionalities are supported of a content-based image retrieval system: data extraction processing, query processing and relevance feedback.

The data extraction processing is the first step, it is responsible for extracting low-level features $j = 1, 2...m$ (such as color, texture, shape, etc.) describing as best as possible the content of each image i. Features are expressed by corresponding numerical values, and are grouped into appropriate feature vector $[F_i = F_{i_1}, F_{i_2}...F_{i_m}]$ where F_{ij} is the value of the position j from feature vector corresponding to query q_i. This process is usually performed off-line.

The query processing, in turn, extracts a feature vector from a query and applies a metric (such as the Euclidean distance) to evaluate the similarity between the query image and the database images. The similarites scores of the query results builds a score vector. A score vector S_i of an image i can be thought of as a set of scores $[S_i = S_{i_1}, S_{i_2}...S_{i_n}]$, where n is the dimension of database images.

In this paper, we focus on how to represent the query by using its features and its score vector.

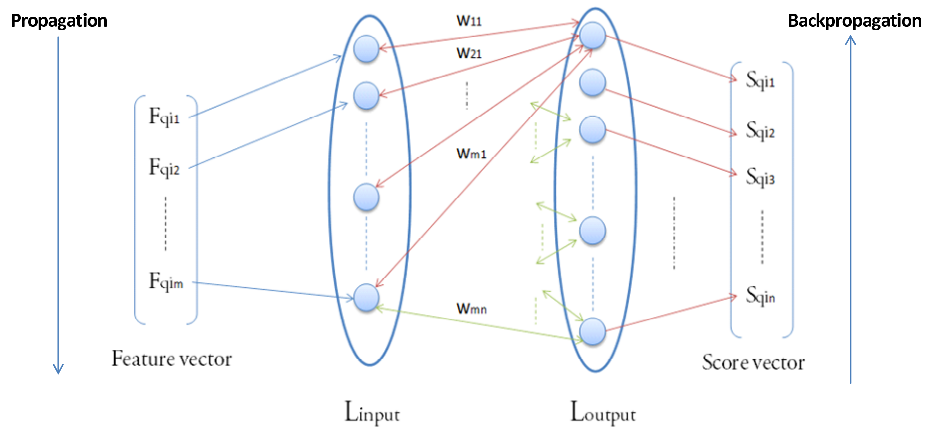

Fig. 1. General system of neural network model proposed

B. Image retrieval based on neural networks

For neural network construction, we need a set of queries $q_1, q_2 ... q_n$. Each query q_i is expressed on the feature vector by $F_{q_i} = [F_{q_{i1}}, F_{q_{i2}}, ..., F_{q_{im}}]$, where $F_{q_{ij}}$ is the value of feature in the query q_i. The image retrieval process provides a score vector $S_{q_i} = [S_{q_{i1}}, S_{q_{i2}} \dots S_{q_{in}}]$, where $S_{q_{ij}}$ is the value of similarity score between the query q_i and the image j where $j \in \{1..n\}$. We assume that each image retrieval algorithm is associated with a vector space model providing the same image ranking.

This vector space model is characterized by a $(m \times n)$ matrix W where for each query q_i, described by F_{q_i} feature vector, associated with a score vector S_{q_i}, we have:

$$F_{q_i} \times W = S_{q_i} \quad (1)$$

In this paper, we attempt to predict matrix W over a set of queries (a set of queries for training phase and a set of queries for validation phase) and their associated score vectors S_{q_i}. To solve equation 1, we build a neural network containing 2 layers.
L_{input} is the input of the network containing the F_{qi} values and L_{output} is the ouput of the network containing the S_{qi} values. Figure 1 shows our neural network. The application of a learning approach in this neural network on a set of queries led to matrix W, where w_{ij} is given by equation 2:

$$W[i,j] = w_{ij} \qquad \forall (i,j) \in \{1,2...n\} \times \{1,2...m\} \quad (2)$$

$$\begin{pmatrix} F_{q_{i1}} \\ F_{q_{i2}} \\ \vdots \\ F_{q_{im}} \end{pmatrix} \times \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nm} \end{pmatrix} \cong \begin{pmatrix} S_{q_{i1}} \\ S_{q_{i2}} \\ \vdots \\ S_{q_{in}} \end{pmatrix}$$

The w_{ij} values are initialized with a random values. These values are then calibrated by using a learning process. For each query q_i represented by $F_{q_i} = [F_{q_{i1}}, F_{q_{i2}}, ..., F_{q_{im}}]$, we propagate $F_{q_{ij}}$ values through the neural network in order to compute $S_{q_{ij}}$ scores (see algorithm 1).
s_j is the actual score,
α is the learning parameter coefficient ($0 \leq alpha < 1$).

Algorithm 1 Propagation algorithm

$\forall (i,j) \in \{1,2...n\}\{1,2...m\}$
$w_{ij} = 1$
for *each* query q_i **do**
  for *each* $F_{qi} = (F_{q_{i1}}, F_{q_{i2}} ... F_{q_{im}})$ and $S_{qi} = (S_{q_{i1}}, S_{q_{i2}} ... S_{q_{im}})$ **do**
    $s_j = \sum_{j=1}^{m} w_{ij} F_{i_j}$
    $w_{ij} = w_{ij} + \alpha F_{i_j}$
  end for
end for

After the learning phase, we use the second set of validation queries which are noisy versions of the training set but aren't used for training. Each time after the network has trained, this set is used to calculate an error (called error backpropagation). This error corresponds to failure between the desired score value and the expected scores (which are provided by the image retrieval process). We use the backpropagation algorithm to calibrate the w_{ij} weights.

This Backpropagation process is done by algorithm 2.

Algorithm 2 Backpropagation algorithm

$\forall (i,j) \in \{1,2...n\}\{1,2...m\}$
$w_{ij} = 1$
for *each* query q_i **do**
  for *each* $F_{qi} = (F_{q_{i1}}, F_{q_{i2}} ... F_{q_{im}})$ and $S_{qi} = (S_{q_{i1}}, S_{q_{i2}} ... S_{q_{im}})$ **do**
    $s_j = \sum_{j=1}^{m} w_{ij} F_{i_j}$
    $\delta_j = s_j - S_j$
    $w_{ij} = w_{ij} + \alpha \delta_j F_{i_j}$
  end for
end for

s_j is the actual score,
S_j is the expected score,
δ is the error rate.
This algorithm will be repeat until the error of the validation set reduces. When the error becomes low the network stops.
Figure 2 shows the idea. The following curve shows that the validation set error reaches a minimum when the network has fully trained. When the network is overtraining the validation

set error starts rising. In fact, it won't be able to handle noisy data.

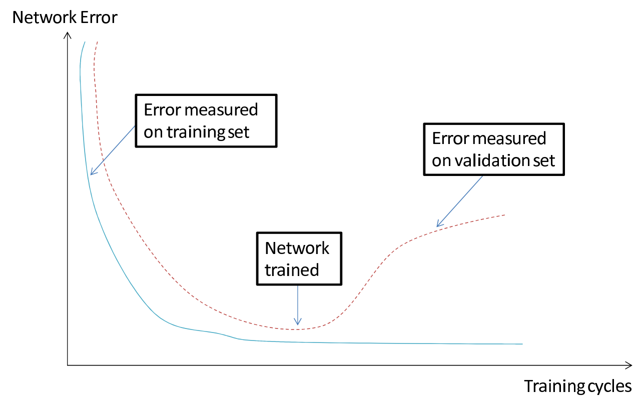

Fig. 2. Use of validation sets

Once the matrix W is constructed, each query q can be calculated directly without applying an Euclidean metric but by applying of equation 1. Thus, the ranks (scores) of resulting images are obtained as a result of multiplication of query feature vector by a weight matrix W.

IV. Evaluation and Results

Our image retrieval system has been implemented with a general image database. The images are stored in JPEG format with size 384×256 or 256×384.

To extract the low-level features from images and queries, we used a color descriptor named CLD [1] and a texture descriptor called EHD [2].

A. Experimental data

For the evaluation, we use two different image corpora for testing our approach: Corel and Caltech-UCSD.

The $Corel$ [3] database in formed by 68040 images from various categories (African people and villages, beach, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and glaciers, food, etc.). An extract of a subset of this dataset is given by figure 3.

The $Caltech - UCSD$ [4] [15] is an image dataset with photos bird species formed with 6033 images from 200 categories. An extract of a subset of this dataset is given by figure 4.

We evaluate our contribution in two ways. First, we judge the choice of training queries (N_{train}) and validation queries (N_{test}) using for matrix building. Then, we compare our approach with two classical systems of CBIR. We note that the queries used to evaluate our model are not taken by training phase.

[1] A color layout descriptor (CLD) is designed to capture the spatial distribution of color in an image. The feature extraction process consists of two parts; grid based representative color selection and discrete cosine transform with quantization

[2] Edge Histogram Descriptor (EHD) is proposed for MPEG-7 expresses only the local edge distribution in the image

[3] https://archive.ics.uci.edu/ml/datasets/Corel+Image+Features

[4] http://vision.caltech.edu/visipedia/CUB-200.html

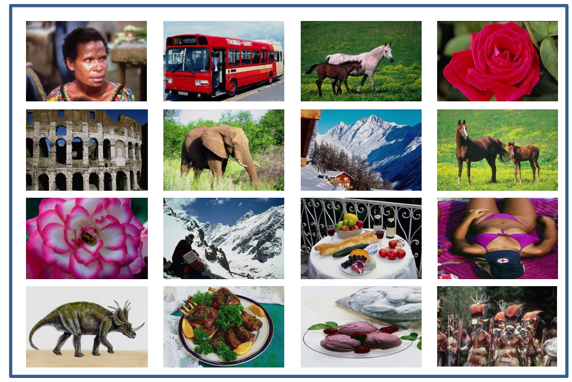

Fig. 3. Example of Corel images used in experiment

Fig. 4. Example of Caltech-UCSD images used in experiment

B. Results

The performances are measured by the MAP (Mean Average Precision). The purpose of our retrieval model is to improve results provided by the initial retrieval model. A commonly arising question regards the number of training images to use for a particular problem. For this, we have divided our dataset into two parts: training set and validation set.
During the matrix W construction, we carried out three tests:

- Test 1: $N_{train} = 50\%$ images and $N_{test} = 50\%$ images.
- Test 2: $N_{train} = 25\%$ images and $N_{test} = 75\%$ images.
- Test 3: $N_{train} = 75\%$ images and $N_{test} = 25\%$ images.

Each test is assigned to our initial retrieval system. Performance for each test can be measured by determining the Mean Average Precision (MAP). The cumulative performance is calculated by counting the total number of relevant image for queries.

Table IV-B presents the MAP for query set used with Corel dataset and Caltech-UCSD dataset. The results of this experiment vary widely between the two dataset, and from one test to another. We notice that with Test 2, we achieved the better results to those obtained with Test 1 and Test 3. The obtained results with test 2 increase compared to other tests. This gain is observed for the Corel dataset (56) whereas with Caltech-UCSD we have (42). This gain emphasises the

TABLE I. PERFORMANCE ACHIEVED BY THE NEW RETRIEVAL MODEL WITH THREE VERSIONS OF TRAINING DATASET

	Corel			Caltech-UCSD		
Images number	68 040			6033		
Queries number	8442			200		
Evaluation	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3
MAP	0.40	**0.56**	0.34	0.29	**0.42**	0.25
Error training rate	*0.22*	**0.19**	*0.49*	*0.33*	**0.24**	*0.46*
Error validation rate	*0.21*	**0.22**	*0.12*	*0.27*	**0.28**	*0.21*

quality and quantity of training examples. This means that the number of N_{train} is an important feature for achieving a high performance of our model.

The images number used for learning the matrix W has impact on training process. When $N_{train} = 50\%$ or $N_{train} = 75\%$, this number is impractically large, therefore, the error training rate increases (Corel 0.22 resp 0.49; Caltech-UCSD 0.33 resp 0.46).

We also notice that training error and validation error are correlated with each other and help in better predicting the obtained results with matrix W and in turn on the quality of results provided by our search model. This proves that the best predictive model would be where the training error and the validation error are close enough and have their global minimum. This is verified for test 2 (Corel: 0.19 resp 0.22; Caltech-UCSD: 0.24 resp 0.28). Table IV-B shows a

TABLE II. RETRIEVAL PERFORMANCE (MAP) OF VARIOUS CBIR SYSTEMS

	MAP	
	Corel	Caltech-UCSD
Initial retrieval system	0.42	0.38
Simple vector space model	0.37	0.21
Vectorisation	0.47	0.35
Our approach	0.56	0.42

comparison of our method with to others CBIR systems. The first system is our initial retrieval system based on euclidien mesure. The second system include a vector space model [21]. The third system include the vectorization process of CBIR [4]. The fourth system follows the search results include images from the expanded queries.

The evaluation results show that our method provides a MAP value better than others retrieval system. Such comparison has a qualitative meaning, since retrieval systems are performed under the same conditions (same descriptors are used to represent features).

V. CONCLUSIONS AND FUTUREWORK

The learning techniques have increasingly seen application in information retrieval systems such as the neural networks. In this paper, we have demonstrated how the neural network can be used in a vector space model to build a new model of content-based image retrieval.

In fact, this model can be used for image retrieval. The main idea of this model is to build a connection between the query image and the result score directly via neural network architecture. This model uses neural networks in order to learn an $m \times n$ dimensional matrix W that transforms a m dimensional query vector into a n dimensional score vector whose elements correspond to the similarities of the query vector to the n dataset vectors. We perform the backpropagation step in the extended network that computes the error function and fixes the weights values.

Experiments are carried out using Corel database and Caltech-UCSD. The comparative experiments show that our model provides a MAP values better than a baseline retrieval model.

The future directions for our work will consist, in first step, in evaluating our new model with a large image collection. In second step, we will examine the benefit of including conceptual information within the new retrieval model.

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