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# Amalgamated Framework for Retrieval of Two Dimensional Images

T.Sharath[1], J.Raghavendra Prasad[2], Raviranjan Singh.K[3],
N.P Sai Prabhakar[4],Mr.S.Sridhar[5]
[1,2,3,4,5]*(Department of Electronics and communication Eng., LIET/ JNTUK, INDIA)*

***Abstract :*** *The World Wide Web has become a vital source for information. Search enginesavailable now a days are giving results based on individual user's search which is user dependent. Here we are trying to refine the search results irrespective of user by considering the user feedback. The refinement results can have lot of advantages and user experience. We can reconstruct the search results with same search query and user feedback. Results are refined in such a way that they are displayed in the order of relevancy.Relevance feedback is a technique to improve the results of retrieval. It uses information from the result of an initial retrieval to modify the query in such a way that more relevant documents are fetched the second time. A user may specify which documents are relevant and which are not. Although relevance feedback (RF) is existing methodology, but it has been extensively studied in the content-based image retrieval community, no commercial Web image search engines support RF.Our framework shows advantage over traditional RF mechanisms in the textual feature-based RF mechanism employs an effective search result clustering (SRC) algorithm to obtain salient phrases, based on which we could construct an accurate and low-dimensional textual space for the resulting Web images.*
***Keywords:*** *Relevance feedback (RF),Search result clustering(SRC), content based image retrieval.*

## I. Introduction

World Wide Web is a very important information tool which comprises/holds many of the informational needs of the users. It provides us with the rich information which includes text, images, graphics, etc. User keeps on searching on web but he/she often fail to get the appropriate results as per the relevancy. Order of display of results will be affected by various issues like commercial, hit count, user ratings etc. In this paper we are refining the search results display order based on relevance feedback.

Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval systems work with whole images and searching is based on comparison of the query. General techniques for image retrieval are color, texture and shape. These techniques are applied to get an image from the image database. They are not concerned with the various resolutions of the images, size and spatial color distribution. Hence all these methods are not appropriate to the art image retrieval. Moreover shape based retrievals are useful only in the limited domain. The "content and metadata" based system gives images using an effective image retrieval technique. Many Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval systems work with whole images and searching is based on comparison of the query. Hence all these methods are not appropriate to the art image retrieval.

Moreover shape based retrievals are useful only in the limited domain. The content and metadata other image retrieval systems use global features like color, shape and texture. But the prior results say there are too many false positives while using those global features to search for similar images. Hence we give the new view of image retrieval system using both content and metadata.Relevance feedback originally developed for information retrieval is an online learning technique aiming at improving the effectiveness of the information retrieval system. The main idea of relevance feedback is to let the user guide the system. During retrieval process, the user interacts with the system and rates the relevance of the retrieved documents, according to his/her subjective judgment. With this additional information, the system dynamically learns the user's intention, and gradually presents better results. Since the introduction of relevance feedback to image retrieval in the mid-1990s, it has attracted tremendous attention in the content based image retrieval (CBIR) community and has been shown to provide dramatic performance improvement. However, no commercial Web image search engines support relevance feedback because of usability, scalability, and efficiency issues.Note that the textual features, on which most of the commercial search engines depend, are extracted from the filename. ALTtext, URL, and surrounding text of the images. The usefulness of the textual features is demonstrated by the popularity of the current available Web image search engine. While straightly using the textual information to construct the textual space leads to a time-consuming computation and the performance suffers from noisy terms. Since the user is interacting with the search engine in real time, the relevance feedback mechanism should be sufficiently fast, and if possible avoid heavy computations over millions ofretrievedimages.TointegraterelevancefeedbackintoWebimageretrievalinapracticalway,anefficientandeffective mehanismis required for constructing an accurate and low dimensional textual space with respect to the resulting images.

## II. Motivation

Due to the increase of online users on the Internet, the amount of collections of digital images have grown continuously during this period, for example, in web applications that allows adding images and digital albums. Also is important to note that the images are globally used. The influence of television, old photographs and games has contributed to this growth as well. Images are increasingly used to convey information, whether one local information, weather, advertising, etc. In this context, it is necessary the development of appropriate systems to manage effectively these collections. Another problem was the complexity of image data, and these data can be interpreted in various ways, thus raising the question of how to work in order to manipulate these data and represent or establish policies to its content. This motivated the birth of the image retrieval area whose goal is try to solve those problems.

## III. Proposed Algorithm

Rocchio's algorithm is used,to perform RF in textual space. The algorithm was developed in the mid-1960s and has been proven to be one of the most effective RF algorithms in information retrieval. The key idea of Rocchio's algorithm is to construct a so-called optimal query so that the difference be-tween the average score of a relevant document and the average score of a no relevant document is maximized. Cosine similarity is used to calculate the similarity between an image and the optimal query. Since only clicked images are available for our proposed framework, we assume clicked images to be relevant and define the feature of optimal query as follows:

$$\overrightarrow{F_{\mathrm{opt}}} = \overrightarrow{F_{\mathrm{ini}}} + \frac{\alpha}{N_{\mathrm{Rel}}} \sum_{I \in \mathrm{Rel}} \overrightarrow{F_I} - \frac{\beta}{N_{\mathrm{Non-Rel}}} \sum_{J \in \mathrm{Non-Rel}} \overrightarrow{F_J}$$

The textual feature-based RF mechanism employs an effective search result clustering (SRC) algorithm to obtain salient phrases, based on which we could construct an accurate and low-dimensional textual space for the resulting Web images. As a result, we could integrate RF into Web image retrieval in a practical way. The images collected from several photo forum sites, e.g., photo sig, have rich metadata such as title, category, photographer's comment and other people's critiques. These images constitute the evaluation dataset for the proposed relevance feedback framework. For example, a photo of photosig[1] has the following metadata. In order to facilitate later citation of this photo, we denote it by $P_{\mathrm{cm}}$.

**Example:**
Title: early morning.
Category: landscape, nature, rural.
Comment: I found this special light one early morning in
Pyrenees along the Vicdessos River near our house .
One of the critiques:wow, I like this picture, very much,I guess the light has to do with everything
The light is great on the snow and on the sky(strange looking sky by the way) greatly composed, nice, crafted border, a beauty.All the aforementioned metadata is used as the textual source for the textual space construction. To build the textual space, there are two available approaches in our work. One straight-forward approach is directly using the above metadata to obtain the textual feature.
To represent the textual feature, vector space model with TF-IDF weighting scheme is adopted. More specifically, the textual feature of an image $I$ is an $L$-dimensional vector and can be given by

$$F^T = (w_1, \ldots, w_L) \qquad (1.1)$$

$$w_i = tf_i \cdot \ln(N/n_i) \qquad (1.2)$$

Where:
$F^T$ is the textual feature of an image $I$;
$w_i$ is the weight of the $i$th term in $I$'s textual space;
$L$ is the number of all distinct terms of all images' textual space;
$tf_i$ is the frequency of the $i$th term in $I$'s textual space;
$N$ is the total number of images;
$n_i$ is the number of images whose metadata contains the $i$th term.

To illustrate the straightforward approach where all metadata is utilized to construct the textual space, we use the photo $P_{\mathrm{cm}}$ introduced at the beginning of this section as an example. Given the query "early morning," we have 151 resulting images including photo $P_{\mathrm{cm}}$. Based on those resulting images, we collect all distinct terms from the metadata which results in totally 358 distinct terms. For $P_{\mathrm{cm}}$, it has 48 distinct terms, which consist of early, morning, landscape, nature, rural, I, found, this, special, light, one, in, Pyrenees, along, the, Vicdessos, river, near, our, house, wow, like, picture, very, much, guess, has, to, do, with, everything, is, great, on, snow, and, sky, strange, looking, by, way, greatly, composed, nice, crafted, border, a, and beauty.Given $\mathrm{N}{=}151\mathrm{L}{=}358$, and 48 distinct terms of $P_{\mathrm{cm}}$, we can calculate $tf_i$ and $n_i$ for each distinct term with respect to $P_{\mathrm{cm}}$. As a result, we can obtain $w_i$ according to the (1.2). In the end, according to the (1.1), the textual feature $F^T$ of $P_{\mathrm{cm}}$ is obtained.

To construct an accurate and low-dimensional textual space for the resulting Web images, we use the SRC algorithm pro-posed in [19]. The author re-formalizes the clustering problem as a salient phrase ranking problem. Given a query and the ranked list of search results, it first parses the whole list of titles and snippets, extracts all possible phrases ($n$-grams) from the contents, and calculates five properties for each phrase. The five properties consist of phrase frequency/inverted document frequency (TFIDF), phrase length (LEN), intra-cluster similarity (ICS), cluster entropy (CE), and phrase independence (IND). The five properties are supposed to be relative to the salience score of phrases. In our case, the comment and critiques are regarded as snippets. In the following, the current phrase is denoted as $w$, and the set of documents that contains $w$ as $D(w)$. Then, the five properties can be given by

$$\mathrm{TFIDF} = f(w) \cdot \log \frac{N}{|D(w)|}$$

$$\mathrm{LEN} = n$$

$$\mathrm{ICS} = \frac{1}{|D(w)|} \sum_{d_i \in D(w)} \cos(d_i, c)$$

$$c = \frac{1}{|D(w)|} \sum_{d_i \in D(w)} d_i$$

$$\mathrm{CE} = -\sum_{t} \frac{|D(w) \cap D(t)|}{|D(w)|} \log \frac{|D(w) \cap D(t)}{|D(w)|}$$

$$\mathrm{IND} = \frac{\mathrm{IND}_l + \mathrm{IND}_r}{2}$$

$$\mathrm{IND}_l = -\sum_{t=l(W)} \frac{f(t)}{\mathrm{TF}} \log \frac{f(t)}{\mathrm{TF}}$$

Where $f$ represents frequency calculation.Given the above five properties, we use a single formula to combine them and calculate a single salience score for each phrase. In our case, each term $x$ can be a vector $x{=}(\mathrm{TFIDFLENICSCEIND})$. A regression model learned from previous training data is then applied to combine the five properties into a single salience score $y$. When comparing the performance of linear regression, logistic regression, and support vector regression, the performance of linear regression is the best one. Therefore, in our experiments, we choose the linear regression model. The linear regression model postulates that

$$y = b_0 + \sum_{j=1}^{p} b_j x_j + e$$

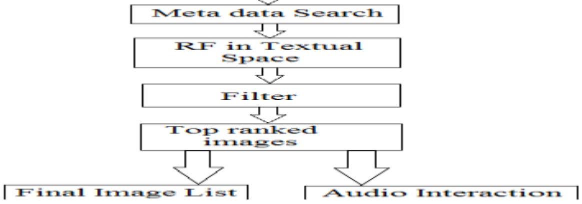
where:

$e$ is a random variable with mean zero;

$bj$ is a coefficient determined by the condition that the sumof the square residuals is as small as possible.

The phrases are ranked according to the salience score $y$, and the top-ranked phrases are taken as salient phrases. The resulting salient phrases are utilized to construct the textual space.

**Flow ofthe Algorithm**



## IV. Explanatory Results

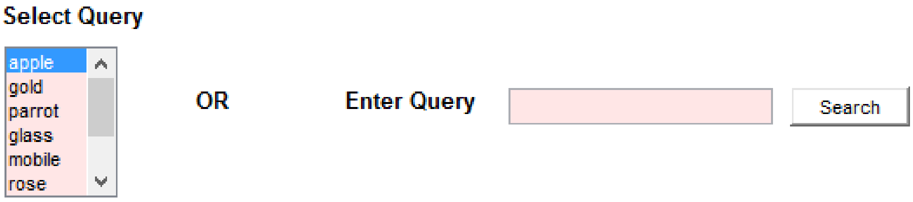



**Fig.1.Audio:** "Welcome to the search menu."

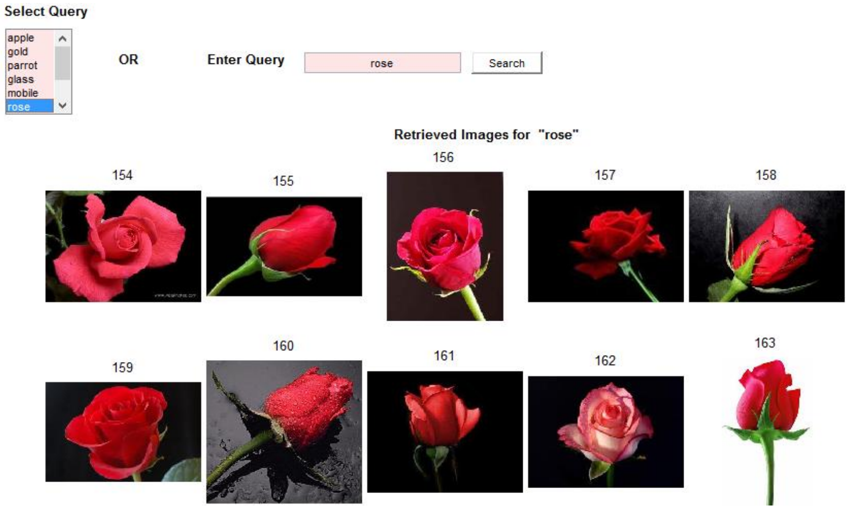



**Fig.2.Audio: "**Here are results for your search."

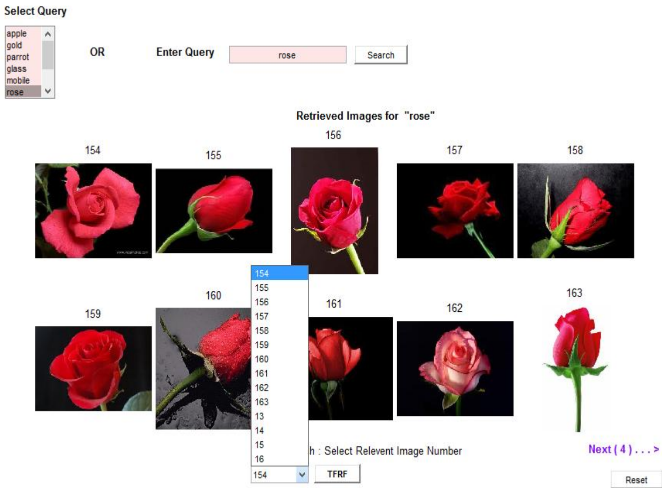



**Fig.3:** Textual based Image retrieving.

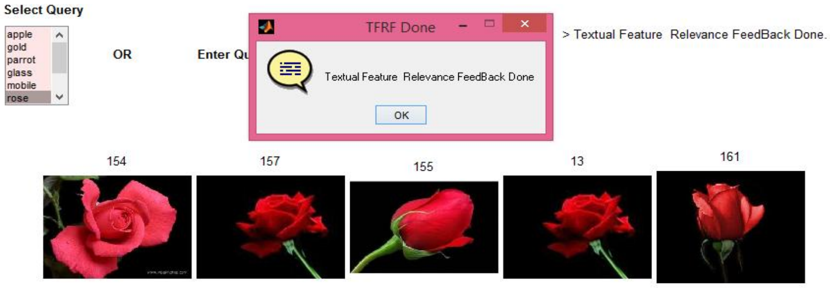



**Fig.4:** Textual Feature Relevance Feedback Done.

## V. Conclusion

In this paper, we have presented a relevance feed-back framework for Web image retrieval. During RF process, textual features based ranking process takes place. To integrate RF into Web image retrieval in a practical way, the textual feature-based RF mechanism employs an effective search result clustering (SRC) algorithm to construct an accurate and low-dimensional textual space for the resulting Web images. Besides explicit relevance feedback, implicit relevance feedback, e.g., click-through data, can also be integrated into the proposed mechanism. Then, a new user interface (UI) is pro-posed to support implicit RF. Experimental results on a database show that the proposed mechanism is wieldy, scalable, and effective.Security applications, Multimedia, Culture, art and educationand Telecommunicationsarethe wide areas now a days this proposal is probably applicable.

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