# Fast retrieval of multi- and hyperspectral images using relevance feedback

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*Abstract-* **A high speed of retrieval is very important to developing an effective image cube search algorithm for the remote sensing community. Following the work of Berman and Shapiro, it is shown that a triangle inequality search technique applied to a relevance feedback retrieval algorithm can significantly speed up the search for and retrieval of physical events of interest in large remote-sensing databases. An improvement in retrieval speed is illustrated using hurricane queries applied to the multispectral GOES database.**

## I. INTRODUCTION

The search for and analysis of unique physical events, observed in multi- and hyperspectral remote sensing imagery, can be significantly aided through the use of fast, efficient, content-based image retrieval (CBIR) algorithms. These algorithms are designed to find a set of spatial/spectral image cubes from a very large database that most closely resembles a query cube chosen as representative of a physical event of interest, e.g., a fire or a hurricane. Using a GOES hurricane query, this paper demonstrates the capability of a "speed-enhanced" search algorithm to streamline cube retrieval.

Alber et al [1] showed examples of the improvement in retrieval efficiency that can be obtained using the "human-in-the-loop" relevance feedback (RF) procedure, developed by the University of Illinois [2,3] to augment a basic CBIR search algorithm. Three low-level feature vectors or indexes – (a) spectral mean, (b) spectral variance, and (c) image texture – were chosen to represent the high-level visual content of each stored image "tile." The effectiveness of the search algorithm was measured against two sets of multispectral images: (1) GOES weather satellite data [4] (five bands of space-time data of hurricane events, Figs. 1 and 2); and (2) MODIS airborne simulator (or MAS) images of fires from NASA's SCAR-B Brazilian rain-forest campaign (50 bands).

Note that in the infrared, the GOES hurricane "query" has a unique spatial/spectral signature: cold cloud tops rotating around a warm hurricane eye (bands 2-5 in Fig. 2).

More complex object/class vector extraction algorithms have been effectively demonstrated in (a) the versatile GeoBrowse image-retrieval system of Marchisio and Li [6], and (b) the Bayesian probabilistic framework of Schröder et al [7]. The stored feature vectors of both approaches are derived from the calculated properties of certain algorithm classified material groups (e.g. water, grass, or trees).

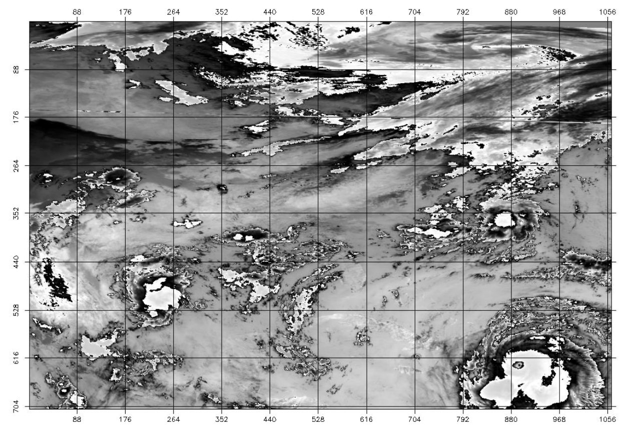


**Fig. 1. GOES-8 image, U.S. East Coast, September 22, 1998. Full GOES scene. Band 4 is displayed.**

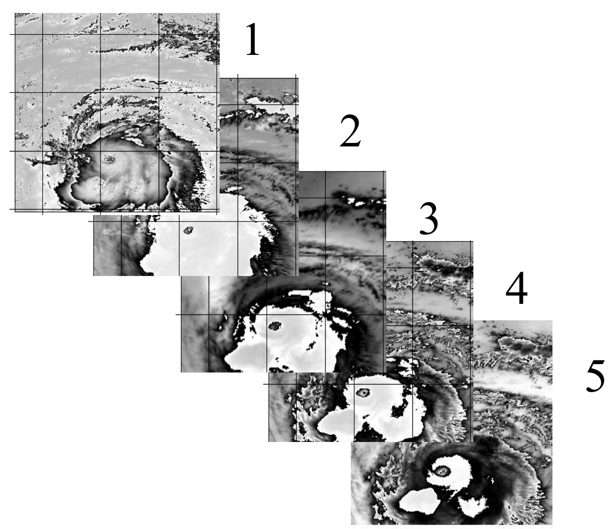


**Fig. 2 User selects query tile centered on Hurricane Georges' eye. Image cube consists of five GOES bands. Wavelengths of the visible and four IR bands are: 0.65, 3.9, 6.7, 10.7 and 12.0 microns. Tile dimensions are 88x88 pixels.**

A number of important challenges still must be addressed in order for CBIR/RF, or any leading image retrieval algorithm, to develop into a fully useful tool for remote sensing analysts. First, the algorithm must demonstrate good retrieval performance and improve its retrieval effectiveness after the relevance feedback, or training, step. Next, the retrieval needs to be quick and user friendly (section II). The following is a brief description of the CBIR/RF process. A sample measure of retrieval performance is presented for the GOES database.

After the user selects a hurricane query cube, the CBIR search engine (using preset index weights) is invoked to retrieve the initial result set [1]. The top 19 images closest in Euclidean distance to the query cube are then displayed. The analyst then ranks the displayed image cubes based on his/her subjective evaluation of the displayed cubes from round one. Those cubes that are deemed to be close in physical character to the query cube are given a high score. Those that are not like the query hurricane are given a low or zero score. The RF engine then updates the query vector weights based on the user specified rankings. A new set of image cubes is retrieved. The cubes are ranked by distance from the query and are displayed as shown in Fig. 3. The process is repeated until convergence.

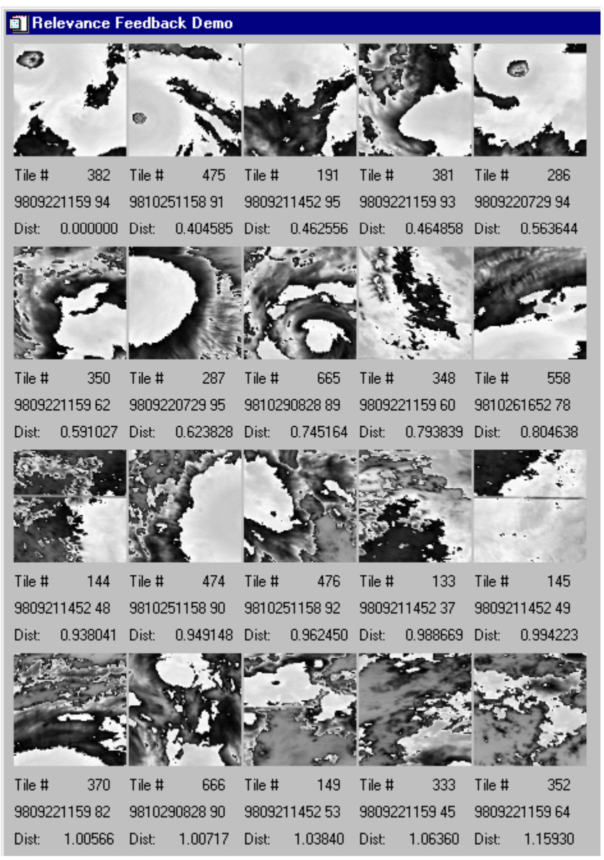


**Fig. 3. Results of the Relevance Feedback process for the GOES Hurricane Georges dataset (search of 672 tiles). The query tile (upper left corner) + 11 retrieved relevant (i.e., hurricane) tiles. All three feature vectors (spectral mean, variance, texture) are used.**

Fig. 4 shows precision, the principal performance metric, for our problem. Note that precision(scope) improves after the user-directed relevance feedback is applied in rounds 2 and 3. Precision(scope) is defined as the number of retrieved relevant images divided by the user prescribed scope (or number) of displayed images. In our case, scope = 20.

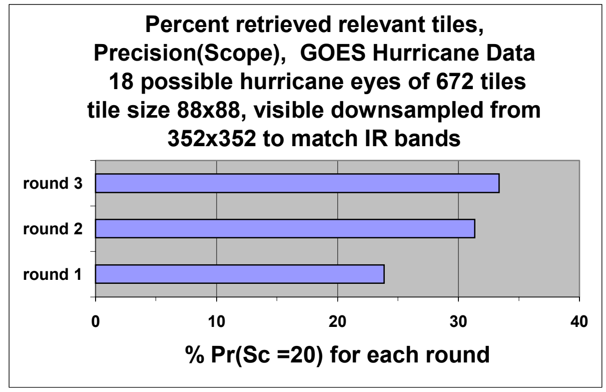


**Fig. 4. Precision for "standard" GOES hurricane retrieval experiment. CBIR (round 1) and relevance feedback (rounds 2 and 3).**

## II. SPEEDING UP RETRIEVAL

High on the list of desired performance characteristics for a good search engine is the need for a fast, efficient image retrieval algorithm.

For any image retrieval code to be regularly utilized by the analyst community, the code must perform its functions quickly and efficiently. A single retrieval process should be concluded in a matter of a few seconds at most, not minutes, even for very large image cube files. The principal factor in determining retrieval speed is the time consumed in calculating the distances (e.g., Euclidean) between the query vector and each of the image vectors stored in a large database.

Berman and Shapiro [8,9] utilized the triangle inequality technique, first introduced by Burkhard and Keller [10], to significantly reduce the number of direct distance calculations needed for an efficient search algorithm. The basis of this technique is that the distance between the query and the image index vectors cannot be less than the absolute value of the difference between (a) the distance between the image vector and a designated object known as a "key," and (b) the distance between the query vector and the same key or keys.

Using the lower bound of the triangle inequality theorem allows the search algorithm to discard a substantial number of images in the feature space that are found to be too far from the query image to be a possible match. Berman and Shapiro also showed that further search efficiencies are possible by taking advantage of a data structure called the triangle trie to reduce the number of operations [8].

Recent work performed at the University of Illinois by Xiong, Zhou, Pottenger, and Huang [11] has adopted the triangle inequality algorithm approach of Berman and Shapiro to speed up a University of Illinois CBIR code with relevance feedback. The feature-weight-updating part of the RF scheme was modified to allow for the incorporation of the triangle inequality algorithm. The code was tested against the Corel dataset, popular with the CBIR community.

Based on Xiong's work [11], estimates have been made of the speedup in performance of a triangle inequality algorithm (augmented by a triangle-trie extension). For a poorly structured index file, it is estimated that it would take over 2 minutes to calculate about 60,000 distance measures. Using the triangle inequality algorithm, it is estimated that the time to calculate those 60,000 distances can be reduced to approximately 1 second.

In our timing study, we used 10 keys for the GOES search problem. These keys were selected offline using a form of the "k-means" unsupervised clustering algorithm. For this algorithm the user sets the desired number of classes. According to Berman and Shapiro [8], the Cluster algorithm provides the best keys for texture measures, while the Greedy algorithm provides the best keys for performance based on image color. Texture was found to be an important feature vector for our GOES hurricane problem, but not in the previous MODIS fire study [1].

Preliminary results using Xiong's technique applied to the GOES-8 hurricane retrieval problem, are presented in Table 1. Retrieval speedup is estimated to be greater than a factor of 5 for large datasets where the time to draw the images will be small compared to the search and distance calculation times. The absolute execution time will, of course, depend on the speed of the computer used, the I/O architecture, and the programming efficiency of the search software.

**TABLE 1.**

**COMPARISON OF EXECUTION TIMES**
**Three feature vectors, 672 tile GOES Image dataset, 88x88 pixels**
**Query tile: 9809221159 # 94 (Hurricane Georges' eye)**
**10 keys used in Triangle inequality algorithm**
**IBM 300 MHz PC**

| Type of processing | Running Time (sec) | |
|---|---|---|
| | Total Time to complete RF Round 2 (Includes time to draw images) | Time to Search and Calculate Feature Vector Distances (exluding drawing time) |
| Standard CBIR+RF | 26.8 sec* | 23.7 sec |
| Triangle Inequality Algorithm | 7.9 sec** | 4.5 sec |
| Speedup Ratio | 3.4 | 5.3 |

***Total process time for a 9510 tile set using standard code = 338 sec.**

**** Estimated process time: 9510 tiles using Triangle Inequality = 63 sec.**

## III. SUMMARY

The estimates of triangle inequality speedup presented in this paper indicate that the CBIR/RF procedure, or other query by example algorithms, have the potential to quickly and effectively retrieve unique physical features (such as hurricanes) from large remote sensing image databases. Our near-term goal is to pursue further algorithm speedups along lines suggested in [9]. In this way we hope to provide a high-speed, high-performance search algorithm to quickly retrieve complex physical events of interest for further analysis by the remote sensing community.

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