A Framework for Geospatial Satellite Imagery Retrieval Systems

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Abstract— **This paper presents a framework for the efficient retrieval of satellite imagery from large-scale databases. With the ever-expanding volume of imagery being acquired from satellite platforms it has become increasingly important to locate specific areas of interest within a large database of images. Identifying relevant areas within image databases can be thought of as finding the "needle in the haystack" problem; too often for a particular task or application there exist a small number of useful images hidden among millions of images. The motivation behind the work presented here is that through the use of geospatial image retrieval systems, the number of scenes that image analysts must manually examine may be decreased dramatically. By using a geospatial image retrieval system as a tool, analysts no longer must manually examine the entire database of imagery, but instead can limit their search to a subset identified by our retrieval system. The techniques that are introduced in this paper have been developed in our image retrieval system named GeoIRIS: Geospatial Information Retrieval and Indexing System.**

I. Introduction

The task of identifying relevant imagery in a geospatial, satellite imagery database is extremely challenging. In many cases simple formulation of potential queries as linguistic descriptions or as sets of numeric constraints may be difficult. An alternative query mechanism is a technique known as content-based image retrieval (CBIR). One method of querying in CBIR–known as query by example–consists of using an image as the query input. Phrased another way, CBIR querying seeks to identify images which look similar to a given image. To accomplish this, the GeoIRIS framework incorporates feature extraction, information indexing & retrieval, and image visualization.

Two other prominent geospatial retrieval systems are Image Query (IQ) [1] and Knowledge-driven Information Mining (KIM) [2]. While IQ relies on user perception and depiction of objects, GeoIRIS automatically exploits both the anthropogenic and landcover features to query. Alternatively, KIM works by performing per-pixel classifications to complete its retrievals, applying data mining techniques over medium-resolution imagery; GeoIRIS provides increased retrieval capabilities by addressing retrieval in the high-resolution domain.

The remaining sections of the paper are organized as follows. Section II provides an overview of the GeoIRIS framework. The techniques used for querying in GeoIRIS are discussed in Section III. The presented framework is analyzed in Section IV and finally, concluding remarks are presented in Section V.

II. GeoIRIS Components

The GeoIRIS framework links several major components involved in the process of geospatial image retrieval. This section details the interworkings of each subsystem and their interactions. Our framework can be seen in Figure 1.

A. Feature Extraction

In order to understand the underpinnings of our geospatial imagery retrieval system the image ingestion and preprocessing process must be understood. This set of steps encompasses the tasks required to extract information from imagery for inclusion in our indexing structures. Pan-sharpening [11] is performed to increase the quality of data available. For example, this allows 0.6 m panchromatic imagery to be used to transform 2.4 m multi-spectral imagery to 0.6 m pan-sharpened multi-spectral imagery. Following the pan-sharpening step, the imagery is subdivided into more manageable tiles. The tile size chosen in GeoIRIS is 256 by 256 meters. This allows tiles to cover a fairly large area yet still contain very localized features. If the tile size is chosen too large, then the features extracted provide little discriminative value as local characteristics are outweighed by the general appearance of an image. The scenes should be tiled in such a way that the tiles overlap one another; this helps reduce the potential problems stemming from cases where important features may lie on a tile edge.

Following image tiling, each tile is used as input to the various feature extraction modules developed. Currently there are four types of features that are extracted in two general classes. The first class of features comes from traditional computer vision algorithms. Spectral features are extracted as a means of measuring color information in the images. Additionaly, co-occurrence texture measures [5] are calculated. The second class of features used in GeoIRIS are anthropogenic. The first of these features are linear features based on the work in [9]. These features capture information about linear structures in an image including direction and the relative strength of the linear structures (e.g. is there a single long, skinny object or many shorter linear objects). Using these features it is possible to easily identify structures such as highways and roads. The second important type of feature in the anthropogenic class is

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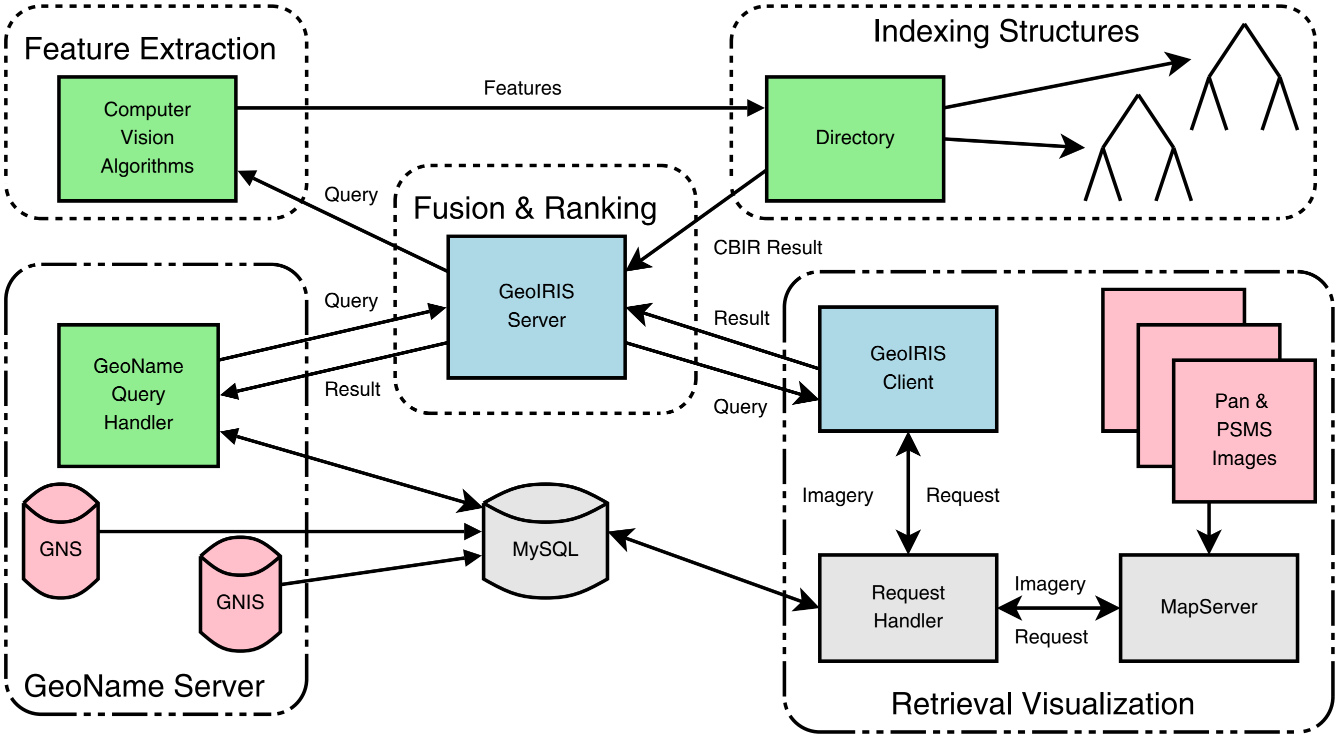

Fig. 1. GeoIRIS System Architecture. The modules of GeoIRIS are shown along with their interactions.

Aggregate DMP features. Derived from algorithms presented in [7], the Aggregate DMP is a tile level feature that captures the relative number of objects present at several different spatial scales. These features are useful in identifying images with objects of the same scale as those found in the query tile. Together these four classes of features are used to encode information about each tile in the image database.

B. Information Indexing

Features extracted from satellite imagery in the previous step are then used to create indexes that allow for efficient identification of similar images from the dataset. This process is carried out by using an indexing structure known as the EBS k-d Tree [8] which was developed for use in CBIR applications. Each of the types of features extracted are indexed separately. Several of the classes of features described above are actually subdivided. Spectral and textural features are indexed separately for RGB, panchromatic and NIR features. Additionally, the linear features are broken down into two indexes–one for the directional component and the other for the linearity component (which includes the strength of the structures). Lastly, the Aggregate DMP features are partitioned based on the NDVI value of each pixel; separate indexes are created for vegetated areas and non-vegetated areas. In total, this results in 10 distinct indexes.

C. Imagery Visualization

In order for a geospatial image retrieval system to be useful it must include an interface to visualize the query results. GeoIRIS builds its visualization engine on top of MapServer from the University of Minnesota [6]. Because feature extraction was done on imagery subdivided into tiles, images displayed to the user must correspond to the tiles used when the image was originally subdivided. An abstraction layer has been written to wrap the functionality of MapServer and return imagery one tile at a time. This visualization layer also includes functionality that caches frequently used images to prevent repeated requests for MapServer to generate identical images.

D. GeoName Server

Information contained within imagery is only one component of our GeoIRIS framework. Heterogeneous datasets can be incorporated and used in conjunction with our CBIR query mechanisms. Two such datasets that have been incorporated into GeoIRIS are the Geographic Names Information System (GNIS) [3] produced by the United States Geological Survey (USGS) and the GEOnet Names Server (GNS) [4] provided by the National Geospatial-Intelligence Agency (NGA). Together, we collectively call the combined database the GeoName Server. The data provided from this source allows for CBIR queries to be restricted based on constriants given with respect to anthropogenic features in the database.

III. GeoIRIS Queries

Following the framework presented previously, several types of queries are possible. These will be detailed in the following section, along with a description of the user interface.

A. Query Methods

Previous image databases have focused on retrieving images solely using information found in image metadata. For example, these databases allowed users to retrieve imagery with general geographic and/or temporal constraints. The system that we have created allows for more complicated queries that make use of information extracted from the imagery itself. By providing an image as a query, GeoIRIS identifies images that possess similar features to that of the query because it is assumed that images that are similar in feature space are similar visually.

Recall that we indexed each set of features separately; this choice now gives us great flexibility. For example, when searching for an image containing a highway, a user can specify that the results from the index corresponding to linear features should be given more weight. It is important to note that there are two methods for weighting the different indexes: manual and automatic. Using the manual approach, users are allowed to tune the weights by providing a value in the range [0,100]. If the value of 0 is given, then the corresponding index will not be used in the final ranking of results; by increasing this value, the index exerts an increasing amount of influence over the final set of ranked results. Although manual tuning may be useful in some cases, automated weighting is more practical. Index weights can automatically be determined based on characteristics of the query image through the use of data mining techniques.

In addition to providing retrieval results by using multiple CBIR indexes, queries can incorporate additional geographic data from the GeoName Server. Termed "hybrid queries", these queries merge the use of image features and geospatial constraints. For example, one such query consists of querying with an image that depicts an area under construction and providing the constraint that results should only be returned if they are within 3 km of a school. In simple terms, the query is to find areas under construction that are near a school. To accomplish this goal, CBIR is first performed and the results of that query are intersected with the results of the geospatial query; images from CBIR that do not meet the constraint are excluded from the final result set.

B. Query Interface

All of the above components are tied together through the GeoIRIS client and server software. The server side of the system handles tasks including user authentication, query processing, and returning the final ranked result set to the user. Once logged in, the GeoIRIS client allows users to submit a query complete with weights values for the CBIR indexes corresponding the different categories of features. The client handles the process of interpreting the query results and displaying the corresponding images to the user in a variety of formats: RGB, panchromatic, and color-infrared. This interface can be seen in Figure 2. The format of all communication within the framework uses XML for easy interoperability and future expandability. An example of this XML communication can be seen in Figure 3. This figure shows the form of an XML message sent to the client which represents the results of a query. Each record contains the location information of the result along with several attributes which correspond to meta-data for the image. Some of these attributes include the acquisition date, municipality, sensor which acquired the image, and the overall distance score.

IV. Analysis

Analysis of a geospatial image retrieval system should address three major points: accuracy, efficiency, and scalability. Examination of the results after performing many queries using GeoIRIS shows that the system is quite accurate; inaccuracies in the results are rarely errors of commission. However, there may exist some relevant image tiles that are not being correctly retrieved. Broader tests with larger quantities of training data are required to identify the exact accuracy. Analysis of the efficiency of the system is a much easier issue to address. Feature extraction on the tiles in the image database is performed offline and does not effect the performance of query processing. Additionally, the CBIR indexes are built offline. The only portions of query processing that take substantial amounts of time are the stages of combining the query results from multiple CBIR indexes and optionally–if performing a hybrid query–applying a geospatial constraint. The time taken for these tasks is on the order of seconds and is acceptable given the quality of information being provided by the image retrieval system. Finally, scalability is a concern given that such a system can potentially be applied to very large image databases. Currently our database consists of over 40 GB of high-resolution imagery from both the IKONOS and QuickBird satellites. This imagery is currently subdivided into over 70,000 image tiles, yet the underlying indexing structures have proven to support much higher quantities of data. Given that a system built under this framework addresses concerns of accuracy, efficiency and scalability, it is clear that the framework presented provides a useful model for geospatial image retrieval systems to aid in the analysis of large quantities of imagery currently acquired.

V. Conclusion

Retrieval of relevant geospatial imagery is a valuable asset in many applications, such as intelligence gathering. To this end, we have developed the GeoIRIS framework for data retrieval which includes modules for imagery preprocessing, indexing, query handling, and results visualization. The main contribution of this paper is the modularized approach of tackling this problem. Moving forward, other query modalities will be incorporated into this framework including object queries and multi-object spatial relationship queries.

Acknowledgments

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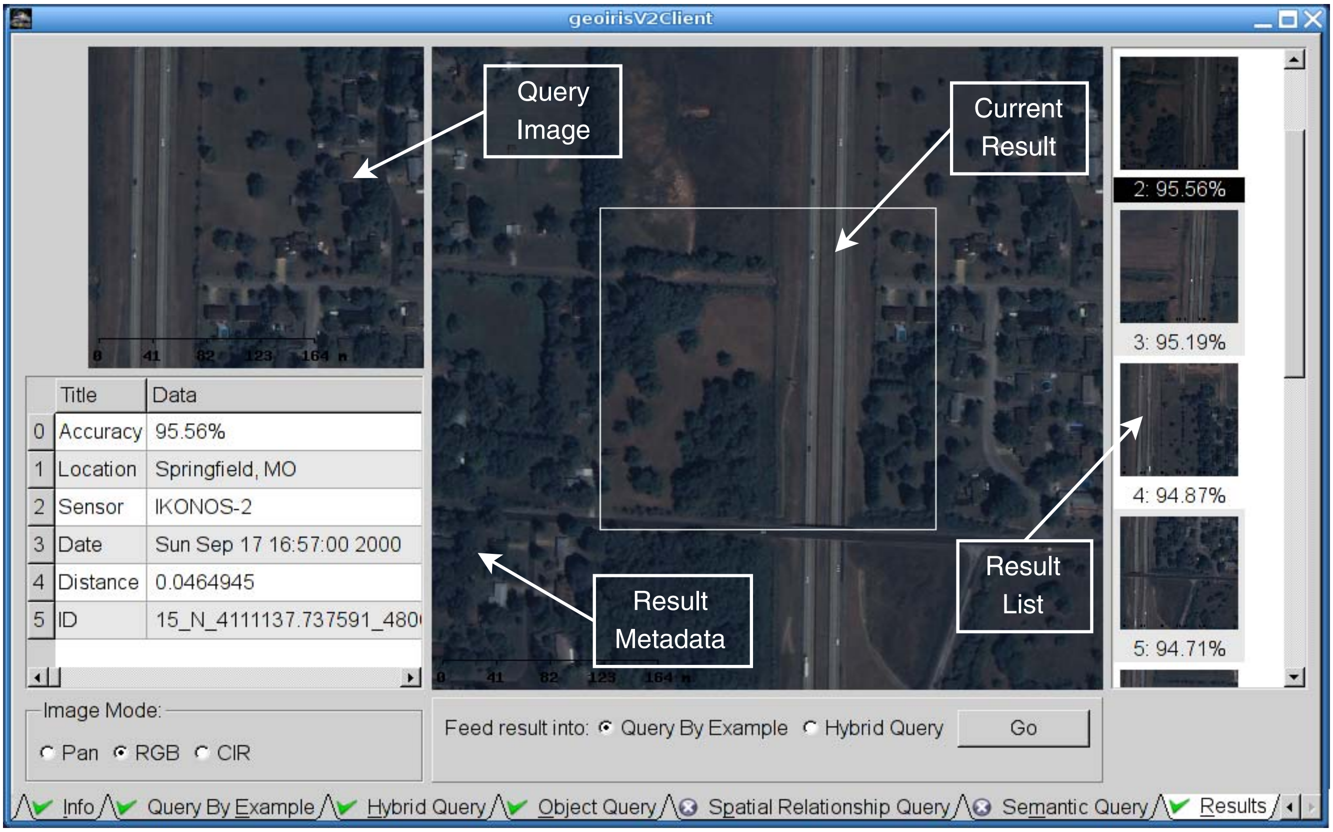

Fig. 2. GeoIRIS Result Interface. Shown in this figure are the results of querying using an image containing a north-south highway and residential housing.


```
<!DOCTYPE hybridQueryResults>
<results>
<record acquisitionDate="Sun Sep 17 16:56:00 2000" dist="0.463902" location="Columbia, MO" distRadius="991.074"
sensor="IKONOS-2" >15_N_4314632.549000_561016.666000</record>
<record acquisitionDate="Sun Apr 30 16:48:00 2000" dist="0.464355" location="St. Charles, MO" distRadius="1575.19"
sensor="IKONOS-2" >15_N_4291786.708000_706363.138000</record>
...
</results>
```


Fig. 3. Above is an example of the XML representation of results from a hybrid query. Each record contains metadata about the corresponding result including acquisition date, location, and sensor. The “dist” field stores the weighted distance based on the CBIR query of multiple indexes while the “distRadius” field contains the proximity of the result to the geographic feature specified in the hybrid query. Lastly, the image key is given and can be used to retrieve imagery corresponding to this location from the Visualization Engine.

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