EARTH OBSERVATION IMAGES INFORMATION MINING FOR FLOODING AND SECURITY RELATED APPLICATIONS

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ABSTRACT

Nowadays the Earth Observation sensors provide images containing detailed information relevant for applications related to hazard or security matters. Unfortunately, image information mining, its interpretation and transformation in products useful to the rescue or decision teams is still a laborious task, effectuated many times by visual inspection and manual annotations of the images, thus not appropriate to react in prerequisite time. This papers presents a knowledge based image information mining concept as a tool, which by interactive operations, enables analysis and interpretation of large volumes of images with high accuracy, flexibility and incomparably much faster than any existing methods. Several scenarios are demonstrated to locate floods in the remote sensing images from Southwestern Romania.

1. PROBLEM DEFINITION

Users in all domains require information to be focused, reliable, low cost and timely, and in a compatible format with the user's own activities. Earth observation data in general and images in particular are retrieved from archives based on attributes such as geographical location, acquisition time and type of the sensor, thus providing no insights into the image's actual information content.

In order to extract information experts interpret images using their own knowledge. In this scenario, the imagery or data sets does not match the customer's real need which is for information. The information extraction process is too complex, too expensive and too dependent on user conjecture to be applied systematically over an adequate number of scenes.

There are domains that necessitate automatic and fast interpretation of the remote sensing data including here the field of humanitarian help.

Flooding is the most common environmental hazard, due to the widespread geographical distribution of river valleys and coastal areas, and the attraction of human settlements to these areas. Earth Observation techniques can contribute to assess properties, infrastructure and agricultural crops damages in flooded areas.

The Earth Observation satellites which include both geostationary and polar orbiting satellites provide a comprehensive and a multi temporal coverage of large areas in real time and at frequent intervals. Thus, they have become valuable for continuous monitoring of atmospheric as well as surface parameters related to floods.

Also it is easier to locate floods in remote sensing images than mapping them from the ground, the process involves more work than drawing a line around what looks like a flood. The water in the satellite images is frequently sitting under a forest canopy or is mixed in with the soil. Often times you cannot see the flooded area until you compare it to an image of the land before flood occurred.

Southwestern Romania was one of the regions hardest hit when the Danube River burst its banks in the spring of 2006. Heavy rain and melting snow pushed the river to record-high levels in many regions. In Romania, snow melt and long lasting rainfalls led to a dramatic increase of water levels at the Danube River to values which were never measured before. More than 4,700 people had to be evacuated from the flooded regions so far, 3,000 of them in the village Rast in the southwest of the country alone. After a dam could no longer withstand the pressure by the water, 600 buildings were flooded from which 115 collapsed.

The purpose of our application is to use a knowledge based information mining system, as a tool, which enables interactively the analysis of large data sets of images in order to identify area with risk to be flooded. We are searching for rivers, lakes and other water courses and for human settlements located near them.

2. IMAGE DATA

The image data we are about to classify were created by US Geological Survey and are Landsat data files in Geographic Tagged Image File Format (GeoTIFF). Each band of Landsat data in GeoTIFF format is delivered as a gray scale, uncompressed, 8-bit string of unsigned integers.

There are seven bands, each of them having ~180MB, imaged area is about 300x300 km\(^2\), 10739 x17739 pixels, 30 meters resolution, representing a large area of
Figure 1. Landsat image ingested in KIM (the first three bands).
Romanian territory. Figure 1 depicts the first three bands of our Landsat data files. The Landsat images of Romania and Bulgaria have very high complexity, both from the point of view of image content and subjective understanding by a user. The data set contains huge diversity of spectral signatures, and a very broad variety of structural information. Most of the structures are natural, having intricate shapes and textures. From the point of view of visual understanding, the scene, for many users, is an un-known scene, and due to the different, geologic, climate, cultural and technological environment, the observed structures are not easy to be understood.

Because of climate, physical characteristics of the region, flood disasters occur very often. Our goal is to obtain a visual risk zone state for this area. We aim to guide people to think alternative settlement places except risk zone. The effects of levees are clearly visible and these data are now available for future planning of levee systems.

Additionally to KIM map panel for image location it is possible to use Google Earth, a 3D interface to the planet, combing satellite imagery and maps, easy to use even for untrained user.

3. KNOWLEDGE BASED INFORMATION MINING CONCEPTS

The image database requires specific interaction with the users, in form of a dialogue that enables the definition of an image semantics adapted to the user conjecture. The KIM system is based on human centered concepts [3] in order to fully exploit the synergy of human-computer: the user guides the interactive learning process and the system continuously gives the operator relevance feedback about the performed training actions and searches the archive for relevant images.

The KIM system is operated in a man machine dialogue based on visual and semantic symbols. In order to adapt to the usual capacity of people to remind sequences of ~7 item, system orders the information and is operated sequentially.

In Fig. 7.1 the KIM system architecture is presented. At time of data ingestion multi mission images are tiled in sub-images, indexed and stored in a repository. From these images, primitive features are extracted, such as spectral, texture and geometrical attributes. To obtain a quasi-complete description of the entire image, textural and geometrical features are extracted at multiple scales.

For data reduction reasons, the features are separately compressed by a global unsupervised clustering across all images in the archive. From the results of unsupervised features classification, we derive a set a signal classes that describes characteristics groups of points in the parametric space of different models. The "vocabulary" of signal classes is valid across all images, ensured by the global-across image classification.

The basic idea of KIM was an application free hierarchical modeling of the image content [4]. The concept of information representation on hierarchical levels of different semantic abstraction is based on a six level Bayesian learning model.

The first three levels of the hierarchical modeling describe the image data D in a completely unsupervised way. Based on this objective representation user subjective interest can be linked to signal classes by probabilities.

A KIM user can interactively learn a semantic cover type of his interest based on a certain combination of pre-selected signal classes of features models, e.g. spectral and texture. This learning procedure is implemented as a man-machine dialogue: the system learns the user conjecture and the user learns the basic properties of the data in archive. In order to allow high precision training specified on full resolution images, an online training interface has been developed.

After a certain semantic label has been defined, the system can make use of this information and apply it to the whole archive the search for relevant images.

![Figure 1. Client server architecture of the image information mining system.](image-url)
4. INFORMATION MINING

This image was introduced and KIM and indexed in 160 sub-images. We use the Map panel for the area definition and for the localization of results. Each and every one of the indexed image is clearly represented on the map by its geographical coordinates, longitude and latitude (Figure 3 a).

The data set covering Romania and Bulgaria can be used for analyzing the eventualities of a flood disaster and the means to react in case of such natural hazards.

Typical tasks for image analysts are to identify flooded land, to look for airstrips to provide humanitarian airborne supply and to detect areas that can be used for building refugee camps.

For optical Landsat TM images we have computed primitive spectral and texture features. Our first goal will be to determine the lakes in the images database. This semantic cover type "lake" can be described very well using spectral features whereas texture captures relevant structures for "city" or "mountain".

In the image panel we select an image containing a lake, from the initial random gallery. For training this semantic cover type the features definition desktop (Figure 3 b) will appear. To perform a very precise training sample we had magnified the image area at the interest location in the zooming panel. The posterior map gives us a feedback about the current state of the trained label. Next step will be the search in the image gallery for images with similar spectral features. A ranked collection of images consistent with the chosen label will be shown (Figure 4).

One may choose a different label that better defines the areas of interest, simply by clicking on it and then on the Choose button. The label will be loaded in the Feature Definition desktop pane. Being satisfied with the trained cover type the user can click on the search button and the data containing the user interaction log is passed to the user management servlets.

Figure 3. a) The Map panel of KIM depicting the area covered by Landsat TM image.

b) The Feature Definition panel of KIM, containing the semantic cover type “lake”.

Figure 4. Resulted image gallery for the semantic cover type "lake".
5. CONCLUSIONS

Floods are among the most devastating natural hazards in the world, claiming more lives and causing more property damage than any other natural phenomena. Several users such as policy makers, researchers, relief agencies and local producers including farmers, suppliers, traders and water managers are interested in reliable and accurate flood information for effective management.

Remote sensing techniques make it possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites. A satellite, which orbits the Earth, is able to explore the whole surface in a few days and repeat the survey of the same area at regular intervals, whilst an aircraft can give a more detailed analysis of a smaller area, if a specific need occurs. Once these data gathered, it would not be much helpful if the processing stage is not timely. New automatic method for feature extraction are needed. We have demonstrated the capacity of a knowledge based information mining system to analyze and explore large volumes of images with high accuracy, flexibility and incomparably much faster than any existing methods.

Further, the integration of information derived from RS techniques with other datasets significantly contributes in the activities of all the phases of flood management.

Acknowledgments

This work was supported by ROSA (Romanian Space Agency) project SATExplore.

Authors acknowledge the support of A.C.S - Advanced Computer Systems S.p.A., Rome, Italy for their support.

6. REFERENCES