Design and Use of Earth Observation Image Content Tools

Mihai Datcu [1, 2], Daniele Cerra [1], Houda Chaabouni-Chouayakh [1], Amaia de Miguel [1],

Daniela Espinoza Molina [1], Gottfried Schwarz [1], Matteo Soccorsi [1]

[1] German Aerospace Center (DLR), Remote Sensing Technology Institute (IMF)
Box 1116, 82234 Wessling, Germany
E-Mail: Mihai.Datcu@dlr.de

[2] Télécom ParisTech
46 rue Barrault, 75013, Paris, France

ABSTRACT

During the last years, it became evident that despite the increasing volume of Earth observation images, a continuous interactive analysis and classification resulting in a semantic labelling of these data is feasible. As a consequence, a number of ESA-financed projects aimed at the interactive semi-automated extraction of user-defined image contents as well as the integration of these capabilities with meta-data descriptor concepts and web-based services. While conventional meta-data annotations provide the capability for browsing among pre-defined entries such as acquisition dates and image coordinates, our new extraction capabilities allow for the systematic annotation and retrieval of scenes containing labelled objects such as ships, airports, or crop types. The typical issues encountered during the development of conventional descriptor concepts appear again: individual solutions will be succeeded by interoperable strategies and co-ordinated efforts are required to cover the various technical peculiarities of active and passive imaging instruments. The article presents the results and experience gained using the Information Mining techniques and functions implemented in the TerraSAR-X PGS system and analyses future issues regarding the multi-mission use of Sentinels and the potential for novel GMES services.

Keywords: remote sensing, earth observation, images, metadata, semantics

INTRODUCTION

Much research has already been done in the image retrieval and image understanding domain in order to bridge the “semantic gap” between digital image data and their content as understood by human observers [1, 2]. This gap describes the lack of direct correspondence between image features and the visual understanding of a scene in terms of higher level content and meaning, i.e., its semantics. Historically, many efforts consisted of deriving visual features adapted to the human visual perception, or of integrating a human in the processing loop by means of efficient active learning algorithms. Researchers concentrated on visual feature-based techniques with no support for semantics-based approaches and ended up with descriptors of basic image features like color, texture, or shape. In the meantime, the explosion of multimedia systems has resulted in a new dimension of how to access the information content of images contained in databases.

In the field of remote sensing and its diverse imaging instruments, we are faced with similar problems [3]. Existing archives contain terabytes of satellite images that undergo routine processing, but - as a rule - will not be analyzed or annotated with respect to their content. While classical metadata annotation provides us with data like the geographical coordinates of image data or technical details about their radiometric and geometric correction, the content of these images remains mostly unexplored. On the other hand, what many users need are automated tools that map digital low-level features into high-level features or maps to allow semantically classified image annotation. The annotations can be used to browse in image archives, to retrieve appropriate images from an archive, to select sub-scenes, and to compare selected scenes. A typical example would be to compare the details of various agricultural scenes, where a selected crop type has been identified.

This content-based search often calls for supplementary data such as external geo-information or digital elevation models; however, we also need databases dealing with multidimensional pictorial structures and pattern recognition algorithms developed from computer vision that provide comfortable database query capabilities. Database queries made by typical users should allow linguistic expressions common to their discipline. In addition, the specific type of an imaging instrument with all its peculiarities will have an impact on the results. For instance, the details contained in an image will depend on the resolution of the instrument; however, what we are aiming at is an instrument independent approach that allows us to handle image content with a unified approach.

In the following, we will describe a toolset system that opens the way towards the semantic annotation and retrieval of remote sensing images. We consider that this kind of approach is urgently needed for the analysis of image data as being expected from ESA's upcoming Sentinel missions.

THE KIM SYSTEM

The Knowledge-driven Information Mining (KIM) system [4] is an image mining system based on Human Centred Concepts (HCC) and employs a Bayesian approach. In essence, it consists of three components:

- a library of algorithms used for the initial feature extraction from ingested images,
- a Bayesian network as the classification component used to generate interactively image classifications, where a user can assign semantic labels,
- a database management system for the image content information catalogue that comprises semantics and extracted knowledge.

The system provides interactive support to extract the user specific relevant information. It also records the accumulated knowledge and can reuse or export it. Moreover, it is designed to operate efficiently with large image archives. Further technical details can be found in [5]. Descriptions of alternative approaches are contained in [6] and [7].

Initially, the KIM system was a stand-alone system that can be installed on medium-sized computers. In the meantime, KIM has been installed at various locations. One installation is at the German Aerospace Center (DLR), where KIM has been embedded with a payload ground segment prototype of a SAR mission. In this configuration KIM offers additional functions such as catalogue and metadata queries, search functions, and visualization of interactively generated results. In future, KIM will also support the analysis of multi-temporal data sets. Further future aspects can be found in the Outlook section below.

A KIM system was also integrated in ESA's Knowledge-centred Earth Observation (KEO) system.

EMBEDDED KIM

KIM can be embedded in a component-based programming environment (KEO) that was designed to build, test and deploy new earth observation services. Its main system components are (cf. Fig. 1):

- a graphical user command interface that includes an image browser, a feature labelling component, and the visualization of various results;
- a KIM system comprising the ingestion chain that manages the ingestion of image products; it interacts with a server to exchange and process data stored in a database. In addition, it includes a feature extraction component that converts images into features, a training interface for feature extraction, and a thematic map extractor;
- several web services;
- a component for additional (selectable) algorithmic processing

The embedded KIM system permits interactive or routine detection of features. One can look for specific features, get image identifiers or feature maps/objects, and store training results. Trained feature labels are linked with semantic terms for storage and retrieval. One can also analyze ingested product data together with their corresponding feature label maps.

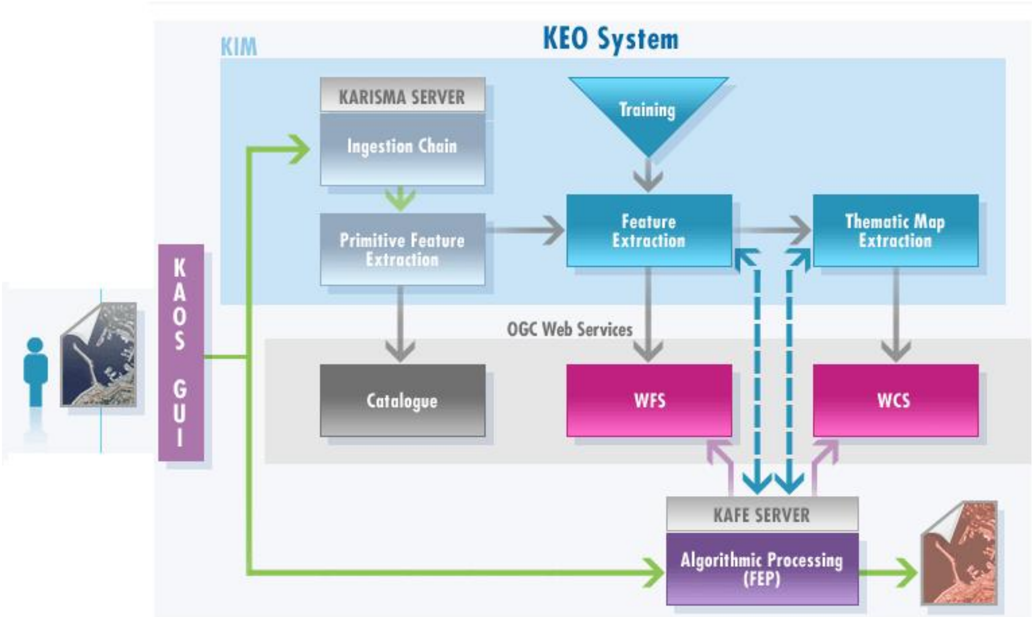

Figure 1: The main building blocks of the KEO system (courtesy of ACS [9])

IMAGE DATA, EXTRACTED FEATURES, AND CONTENT MAPS

In principle, we deal with two types of image data:

- data acquired by optical instruments: in general, we use passive instruments delivering large format images with high resolution in various spectral bands. The high resolution requires large memory during matrix manipulations. Care has to be exercised when comparing images with different processing or calibration levels. During feature extraction, one can use random field models to analyze local image characteristics together with spectral similarity tests. An open field of research is the size of local sub-windows to use for the determination of local image properties.
- data acquired by SAR instruments: in general, we use medium to high resolution data delivering images with a very large number of rows and columns (e.g., strip mode images). The large number of pixels results in remarkable run times during feature extraction. SAR data can be either complex-valued or “detected” (i.e., magnitude) images. In the latter case, speckle noise is a typical phenomenon of SAR images. As a rule, reliable image classification needs despeckled data or estimation techniques that require considerable run time. In addition, the feature vectors being used for feature extraction have to be revised. Special problems occur in high resolution images of urban areas [10].

The extracted features will be clustered by the KIM system to generate similarity classes. This means that we do not aim at a direct one-to-one comparison of pixel-based objects but at a comparison of similar extracted features. Thus, we gain similarity on a higher level that can be linked to semantic classes and allows the generation of semantic maps.

OUTLOOK

For a number of future applications, the KIM system offers good chances to combine the analysis of different types of data:

- the annotation and analysis of several existing data sets of instruments such as Landsat, LandsatTM, ERS-1 and -2, ASAR, TerraSAR-X, etc.

- use of data from upcoming missions such as Tandem providing global or large scale coverage of the Earth;
- the definition of new application fields such as the analysis of image time series (i.e., multi-temporal coverage of selected targets) [11], or the analysis of 3D effects; in particular, high resolution SAR images of built-up areas offer new chances for the recognition of 3D effects;
- new value added products.

When we think about these future aspects we should bear in mind that a universal applicability of KIM requires some care with respect to new value added products. These products should be useful for various users; therefore, they should be "interoperable" for different communities. The different nature of passive and active imaging and the diverse characteristics of imaging instruments have to be assessed prior to the final definition of new products.

At present, many people discuss the various aspects of how to perform and analyze data fusion, for instance, how to fuse optical and SAR image data and how to interpret the results. It should be pointed out that KIM offers new chances by performing data fusion on a semantic level. In this case, a user may avoid the fallacies of conflicting brightness patterns in optical and SAR images.

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ACKNOWLEDGEMENT

The authors gratefully acknowledge the support of ESA and of our project partners during the implementation of KIM and its successor projects.