Image Information Mining: Perspectives seen by DLR

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***Abstract*—Based on our experience with existing image information mining (IIM) systems and their principal building blocks, we propose new implementation technologies for some of their typical functionalities. These new technologies are supposed to be more efficient than existing solutions and offer new performance perspectives. Motivated by potential new applications of TerraSAR-X data, we deal with feature extraction in transform domains, Kolmogorov complexity, hierarchical clustering, and Dirichlet modeling.**

***Index Terms*—Dirichlet modeling, feature extraction, image information mining, hierarchical clustering, Kolmogorov complexity, TerraSAR-X.**

I. Introduction

CURRENT image information mining systems – notably the KIM system [1] designed for satellite image interpretation – have reached a level of maturity and stability that allows their use in operational environments coupled with comparative performance measurements; on their architecture level, the basic component structure and the functionalities offered by each basic component have stabilized.

Therefore, one can already think of next generation systems by exchanging components or devising new general approaches. In this paper, we demonstrate that several new methods are readily available that can be used to improve the efficiency of existing components.

Our investigation was prompted by the recent availability of TerraSAR-X data that contain a variety of new information. The German TerraSAR-X mission is one of the first civilian sources of meter resolution space-borne SAR images.

The images are characterized by high overall and local geometrical stability. As a typical application, the high resolution allows rapid detection and the precise location of ships.

As an example, Fig. 1 shows various ships in the port and the Strait of Gibraltar. One can clearly see the distinct vessel shapes together with telltale point target responses.

These characteristics can be fed into the feature extraction and clustering stages of an IIM system that then provides a comfortable vessel identification system.

The success of the identification strongly depends on the quality and characteristics of high resolution SAR data. Ongoing work aims at the determination of optimal SAR image parameters for automated classification of meter size objects: the image resolution, the radiometric properties, the number of looks, and the parameterization of an IIM system [2].

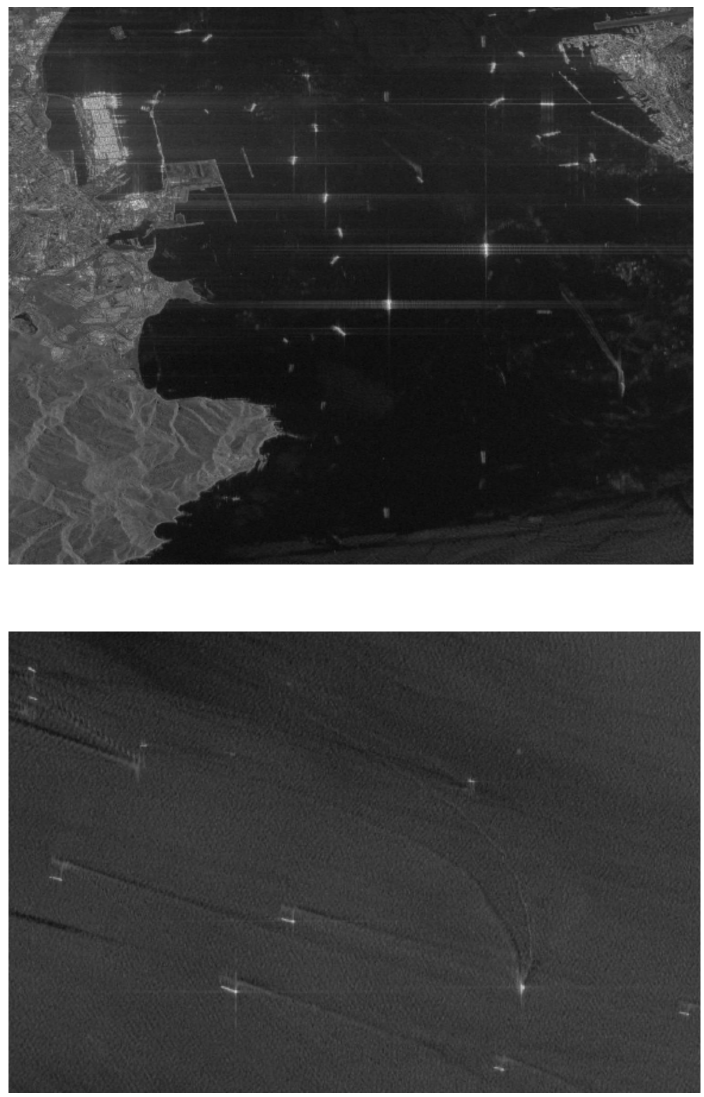

Fig. 1. The port and the Straight of Gibraltar seen by TerraSAR-X (reduced scale).

First of all, however, we have to look at some of the basic requirements of an image information mining system in order to get a better understanding of the layout of such a system.

II. Requirements of an Image Information mining System

A. Operational Aspects

Image information mining systems are characterized by typical requirements that can be grouped into a few categories. One important category for a system to be run in an operational environment deals with its operational aspects. The operational aspects of an advanced image information mining system have to include a number of fully automated functions (e.g., data ingestion, feature extraction, etc.).

B. Machine Learning Aspects

Image information mining systems have to adapt to the general requirements of various user communities and their individual users. Thus, machine learning of object classes, etc. has to include interactive user interfaces, learning of user semantics, retrieval of similar objects, etc.

C. Performance Aspects

Besides the operational aspects already listed above, another important technical category contains performance aspects. This comprises sufficient throughput of image data during ingestion, processing and retrieval. Another critical performance aspect is the robust handling of enormous data volumes.

III. Building Blocks of an Image Information Mining System

The typical building blocks of a current image information mining system for remote sensing data are shown in Fig. 2. In the upper half one can see on the left side the data input component, then the well-known data handling components of feature extraction, clustering, classification, and a semantics component coupled to a user interface.

In the lower half one can see the data base for all images. This data base has to be indexed to allow rapid retrievals of similar scenes and needs a number of support functions providing access to stored images, etc.

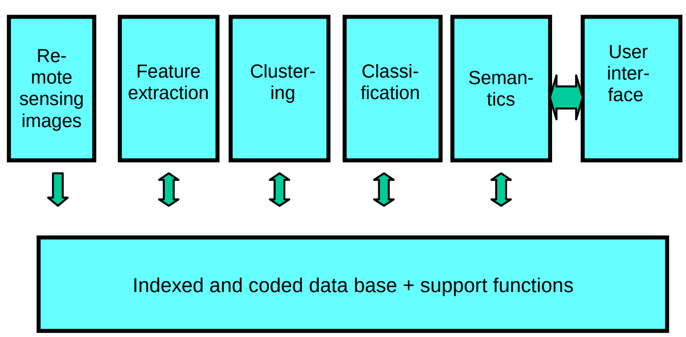

Fig. 2. Typical building blocks of an IIM system.

IV. New Perspectives: Selected Examples

A. Feature Extraction in Transform Domains

Feature extraction can be performed conventionally in the (spatial) pixel domain, or – as an alternative – in a transform domain. The potential advantage of performing feature extraction in a transform domain is to emphasize or highlight details that remain hidden in the original domain, or – what matters most in our applications – to obtain a more compact representation.

Conventional approaches such as Fourier and wavelet transforms are being used by many researchers and do not need to be discussed further. We concentrated on image analysis by Principal Components (PCA) and Independent Components (ICA). Principal Components can be considered as a continuation of the classical linear transform philosophy; in contrast, ICA includes new perspectives how to separate signals [3]. In particular, ICA offers a promising dimension reduction coupled with noise reduction. A typical dimension reduction example of an image time series with repetitive coverage of the same agricultural surface area is shown in Fig. 3. (Top: first three PCs, middle: first vs. second PC, bottom: second vs. third PC).

A critical point that has to be mentioned, however, is a potential drawback of most transform techniques: the results should be invariant with respect to image scale, shift or rotation. This has to be verified carefully.

B. Kolmogorov Complexity

One of the technically less elegant phenomena of an IIM system is a potential cluster fragmentation resulting from ingestions of mixed data. From a system standpoint, compact clusters resulting from feature extraction and distance-based clustering are the preferred choice. Thus, a technique for a seamless concatenation of extracted image primitives with distance measurements during clustering is an interesting alternative.

We can use Kolmogorov complexity [4] as a theoretical criterion to quantify the complexity of a data set (i.e. of an image sub-scene) and then define the similarity between two sub-scenes as a normalized distance based on their individual Kolmogorov complexities:

$$d(x,y) = (K(x,y) - \min(K(x),K(y))) / \max(K(x),K(y))). \qquad (1)$$

Here, d denotes the distance between the sub-scenes x and y, and K stands for the Kolmogorov complexity of a sub-scene. In practice, K of a sub-scene is difficult to compute and can be approximated by the sub-scene compression factor obtained by conventional *gzip* compression. This procedure is illustrated in Fig. 4. The price we have to pay in most cases is a longer run time than in a conventional feature extraction / clustering approach.

C. Hierarchical Clustering

Simple clustering of extracted features can be extended to hierarchical clustering, where we have different levels of clustering [5]. At each clustering level wee see different objects. As illustrated in Fig. 5, at the finest level we can see the objects (*a,b,c,d,e*). At coarser levels, some objects are merged and we can see only the union of previously separated objects.

This technique is helpful when we want to adapt different user semantics to clustered features. Some applications call for fine clustering, while coarse clustering is sufficient for other applications.

D. Dirichlet Modeling and Latent Dirichlet Allocation

Instead of a classical Bayesian maximum likelihood classification, one can use a generative Dirichlet model [6]. As shown in Fig. 6, p$(\theta|T)$ can be represented by a scaled product. For ease of notation, the entire expression can be written in shorthand notation as $Dir(\theta|1+N_1...)$.

Then this θ approach can be used for a description of images [7]: Latent Dirichlet allocation describes an image as a mixture of discovered categories and yields the proportion of each category in an image. Thus, latent Dirichlet allocation can yield a very concise representation of images. An advantage of latent Dirichlet allocation is the availability of algorithms learning and yielding likelihoods of entire databases.

Dirichlet techniques can also be applied to perform incremental learning and un-learning in a dynamic environment.

V. Conclusion

As could be shown above, there exist a number of promising alternative methods for the implementation of typical functions for an image information mining system. On the other hand, current research also has led to a number of innovative approaches that are not yet readily available (e.g., adaptive re-classification). Future systems will tell us which of these ideas will result in efficient implementations.

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Fig. 3. Principal components of a scene (see text).

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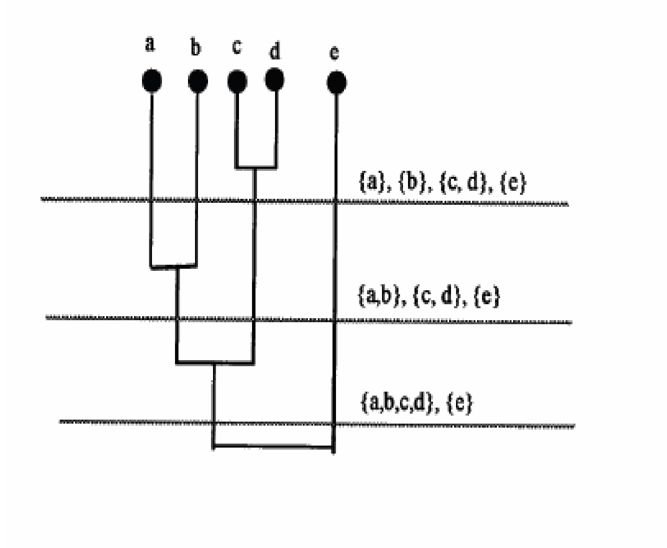

Fig. 5. Clustering with different levels of object visibility.

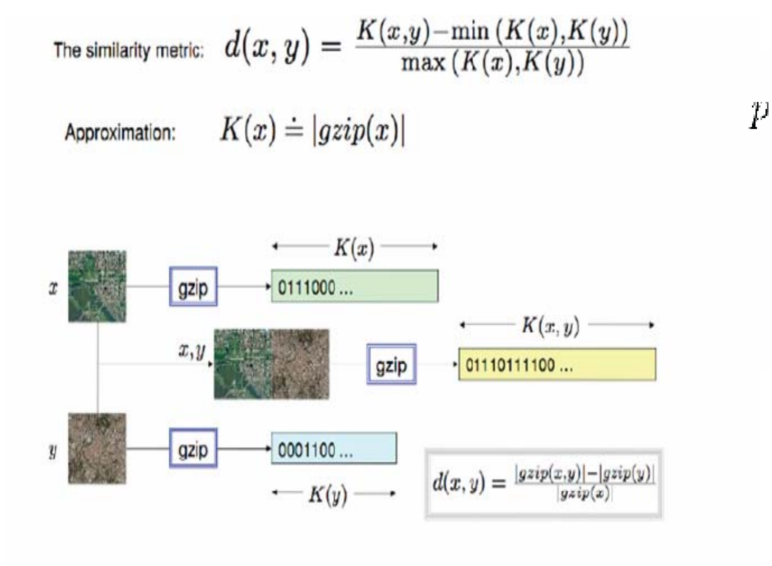

Fig. 4. Use of *gzip* to compute complexities and distances.

$$
\begin{aligned}
p(\boldsymbol{\theta}|T) &= \frac{p(T|\boldsymbol{\theta}) \cdot p(\boldsymbol{\theta})}{p(T)} \\
&= \frac{\Gamma(r+N)}{\prod_i \Gamma(1+N_i)} \prod_i \theta_i^{N_i} \\
&= \mathrm{Dir}(\boldsymbol{\theta}|1+N_1, \ldots, 1+N_r)
\end{aligned}
$$

Fig. 6. Dirichlet formalism.