Abstract
The IIM-TS project has been narrowing the gap between prototypical and user-oriented implementations of multi-temporal analysis algorithms for SITS mining.
Results on real data indicate that the implemented algorithms allow users to effectively exploit the rich content of multi-temporal satellite data in a variety of methodological approaches.

1 Introduction
The evolution of navigation of Earth Observation (EO) archives has been progressing through a number of stages in recent years:

• the archives were first made searchable in terms of metadata
• quicklooks were made available for on-line browsing
• content-based search by well-specified scene targets amenable to detection became feasible
• search by interactively defined scene cover classes was made available to users
• interactive search in terms of scene evolution patterns became possible.

We introduce an implementation of a large scale system that allows all these options to be exercised by users via a simple graphical user interface.

A significant role in the last stages of this evolution process has been played by the Knowledge-based Earth Observation (KEO) systems at the European Space Agency (ESA) [2] [3].
The system has been under active development starting from year 2000, and is currently installed in a number of variants at ESA premises as well as at a number of other institutions all over Europe.
KEO fosters a dual approach to EO archive navigation and exploitation:

• KEO/FEP focuses on integrating a library of well-established distributed batch tool chains for data analysis within a graphic programming environment. This allows users to retrieve elements for which known modeling / detection / inversion algorithms are available.
• KEO/KIM deals with exploratory, user-centered supervised data analysis and interactive scene cover class label retrieval and definition over large archives rather than on single data products.

As of circa 2005, time series mining has been put in the center focus of attention of the EO content-based data retrieval research community, producing award-winning papers and prototypes [1].

ESA has therefore been setting up the Image Information Mining on Time Series (IIM-TS) project aiming at the production of a system capable of providing final users with the analysis and navigation of multi-temporal datasets.
The IIM-TS project has integrated Satellite Image Time Series (SITS) handling and analysis in KEO [2].
2 Image Time Series interactive mining applications

With reference to multi-temporal analysis and GMES scenarios, KEO multi-temporal applications include scenarios such as:

- Ocean current / ocean wind and temperature monitoring and forecasting, ocean colour and harmful alga bloom monitoring, oil spill detection and monitoring
- Flood detection / monitoring / risk analysis, tsunami damage assessment
- Sea ice / land ice motion monitoring and forecasting
- Soil moisture and desertification monitoring
- Land use/land cover change detection, urban monitoring, deforestation and clear cut mapping, crop monitoring and forecasting
- Fire monitoring and risk assessment, burn mapping
- Structural geological mapping, volcanoes monitoring and risk analysis, earthquake damage assessment
- Landslides monitoring and damage assessment, avalanche risk and damage assessment
- Air pollution monitoring
- Hurricane / dust / sandstorm monitoring / risk analysis / damage assessment.

Although many applications are made possible by the procedures of change detection, a number of services require more complex methodologies.

In the case of an analysis of field boundary dynamics, maps of the stability of borders in the series might be generated by supervised discrimination of locally stable borders from unstable borders and registration noise (figure 1).

Finally, isolated events like single airplanes in flight over the imaged scene might be discriminated by their specific characteristics.

As is often the case in EO remote sensing data analysis, issues arise:

- large volumes of EO data get even larger for Satellite Image Time Series (SITS), calling for parallel/distributed high performance processing
- irregular time sampling of the SITS requires proper management of time coordinates of frames.

If both these requirements are taken into account, standard analysis approaches can be extended to the new data: model-based and model-free methodologies can be exploited for conducting the analysis in the spectral/scale, spatial/temporal domains.

3 Multi-temporal hierarchical modeling

The interactive exploratory mapping and analysis algorithms developed in IIM-TS are based on [1].

The authors consider the process of searching and analyzing data in order to discover potentially useful information and approach multispectral image time-series analysis relying on a hierarchical model based information representation.

The concept is based on a hierarchical Bayesian modeling of SITS information content which allows linking the interests of a user to specific spatio-temporal structures. The hierarchy is composed of two inference steps: an unsupervised modeling of dynamic clusters resulting in a graph of trajectories, and an interactive learning procedure based on graphs which leads to the semantic labeling of spatio-temporal structures.
Figure 1: Adam test site near Bucharest, Romania. Field border dynamics analysis in IIM-TS from the CNES Kalideos dataset. Redundancy in the series is exploited, yet the time coordinate direction is not exploited as such.
Figure 2: Isle Reunion, Le Port. Building dynamics analysis in IIM-TS from the CNES Kalideos dataset. Actual MT analysis is performed: the time coordinate associated to the single frames plays a central role in the processing.
Starting from there, the IIM-TS project has attempted a simplification of the concept in order to reach an operational stage.

Instead of a dedicated graph-based supervised classification tool, the standard Naive Bayesian classifier at the core of KIM has been re-used in the context of multi-temporal analysis.

After the basic time-localized features have been extracted by the image information extraction system, they are grouped by similarity, using a simple unsupervised K-Means classification system.

The multiple layers of information thereby obtained have then to be fused with each other: the clusters — here indicated as \( \Omega \) — play the role of an abstract time localized image vocabulary that is able to explain, by different combinations, the set of secondary, multi-temporal features \( \Psi \) that are defined as an additional hierarchical model layer.

Instead of imposing an explicit definition of the phenomenon under study as in a rule-based expert system, descriptions are learnt from the human user by example. This implies a much more direct and powerful way of providing information to the system and enabling it to consider the interpreter conjectures.

To be able to capture the subjective, interpreter-dependent aspects of information, a Bayesian formalization is needed: probability is interpreted as a degree of belief rather than as a frequency of realization. This contextual fusion and interactive classification is performed via a Bayesian classification and fusion system.

The process of interactive learning consists in progressively computing the probability of a specific cover evolution type in the image series, on the basis of positive and negative multi-temporal pixellevel examples provided by the user. The inference process for the label \( S = s_\nu \) given the image series data \( d \) and the features in the clusters \( \omega_i, \psi_j \) is realized through the probability in equation 1 in figure 3. where \( p(S_\nu = s_\nu) \) and \( p(\Psi_j = \psi_j) \) are (usually non-informative) prior probabilities, while \( p(\Psi_j = \psi_j|\Omega_i = \omega_i) \) and \( p(\Psi_j = \psi_j|S_\nu = s_\nu) \) have to be learnt from user examples.

An independence condition is assumed, i.e., the probability is assumed equal to the product of the separate likelihoods for the cover type \( d_\nu \) given each single model since each cover type is considered a combination of different models \( \psi_i = \psi_{M_1} \times \psi_{M_2} \times ... \times \psi_{M_m} \) where \( \times \) denotes scalar product between sets. The same goes for the \( \omega_i \) primitive time-localized features.

If we denote with \( \phi \) the vector parameter which satisfies the identities

\[
p(\psi_i = \psi_i|S_\nu = s_\nu, \Phi = \phi) = \phi_i
\]

and

\[
p(\Phi = \phi) = \Gamma(r)
\]

where \( \Gamma(\cdot) \) is the Gamma distribution, then the probability of the training set is

\[
p(\Phi = \phi|T) = \text{Dir}(\phi|1 + N_1, ..., 1 + N_r) \]

where \( \text{Dir}(\cdot) \) is the Dirichlet distribution and \( N_i \) is the number of occurrences of the signal type \( \omega_i \) in \( T \). If a new training set \( T' \) is provided, the probability is updated according to equation 2 in figure 3.

Denoting with \( a \) the parameter vector which satisfies the identity \( a_i = 1 + N_i \) the learning process is modeled by updating the vector \( a \) after observation of each training set [4].

3.1 Secondary MT features

The generation and handling of secondary features \( \Psi_j \) enables KIM to operate as a multi-temporal analysis engine. The scene evolution understanding, classification and retrieval requires

- the handling of the specific time scale of relevance of the investigated phenomenon (minutes for the passing airplane, days for flooding, seasons for agricultural mapping)
- the proper management of datasets irregularly sampled along time

which implies the need for the definition of temporally and spatially local “validity” masks for the secondary \( \Psi_j \) features to indicate the local availability of data to be able to generate meaningful descriptors for the classification process to take place.

For instance, if the evolution being investigated is defined on a temporal scale of three days (e.g. in the case of flood mapping) and the available data is acquired daily in the first month and then weekly in a second month, then the first two frames in the series will correspond to invalid secondary features (not enough frames before the one under analysis) as will do all of the monthly acquisitions.

Desirable characteristics of a coherent feature set include:
p(S_\nu = s_\nu | D = d) = p(S_\nu = s_\nu) \sum_j \sum_\iota \frac{p(\Psi_j = \psi_j | S_\nu = s_\nu) p(\Psi_j = \psi_j | \Omega_\iota = \omega_\iota) p(\Omega_\iota = \omega_\iota | D = d)}{p(\Psi_j = \psi_j)} \tag{1}

p(\Phi = \phi | T, T') = \text{Dir}(\phi | 1 + N_1 + N'_1, ..., 1 + N_r + N'_r) \tag{2}

Figure 3: Bayesian inference for multi-temporal mining

• the set defines a quasi-complete description of variations / evolutions of cover types as represented in the data

• it implies a natural partitioning of the different phenomena with similarity expressed as geometrical proximity in the secondary feature space

• full feature space spread and independence among the features are strongly desirable.

The basic features identified for the multi-temporal features can be classified into the following categories:

• stability estimators: integrated length of the multi-temporal pixel trajectory along time in the time-localized feature space; volume of convex hull completely containing the time-localized feature space multi-temporal trajectory; edge stability detection and analysis

• feature space trajectory full displacement vector, feature space trajectory fractal dimension estimate

• model based: monotonous trends, seasonal oscillation and local noise decomposition based on a locally weighted regression sampler a la STL [5].

For the very particular case of regularly sampled series, frequency / scale analysis (Fourier frequency ratio, wavelet multi-scale distortion) and time domain autocorrelation can be exploited as well.

The actual choice of primitive and secondary feature spaces considered depends on the application scenario. Agricultural analysis will most probably exploit seasonal decompositions of textural information, while pure change detection might instead employ stability estimators based on spectral descriptors instead.

4 Conclusions

The IIM-TS project has been narrowing the gap between prototypical and user-oriented implementations of multi-temporal analysis algorithms for SITS mining.

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References


