SELF-ORGANISING MAPS FOR CHANGE DETECTION AND MONITORING OF HUMAN ACTIVITY IN SATELLITE IMAGERY

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ABSTRACT

Self-Organising Maps (SOMs) have been successfully applied to content-based image retrieval (CBIR). In this study, we investigate the potential of PicSOM, an image database browsing system, applied to remote sensing images. Databases of small images were artificially created, either from a single satellite image for object detection, or two satellite images when considering change detection. By visually querying those databases, it was possible to detect targets like houses, roads or man-made structures, as well as changes between two QuickBird images. Results open a full range of applications, from structure detection to change detection, to be embedded in a same operative system. The framework may be particularly suitable for long-term monitoring of strategic sites.

Key words: content-based information retrieval, self-organising maps, high resolution satellite images, man-made structure detection, change detection.

1. INTRODUCTION

The increasing number and resolution of satellite sensors to be launched in the coming years will dramatically increase the need for efficient image archiving and processing. Current Earth Observation archiving systems typically support queries by sensor type, acquisition date, imagery coverage or a combination of them. Concurrently, security-concerned applications relying on satellite imagery often demand repeated or continuous monitoring, and intelligent access to the extracted information. There is therefore a growing interest in the remote sensing community to access databases directly by the information contained in images.

Content-Based Image Retrieval (CBIR) allows an efficient management of large image archives [1–6], as well as satellite image annotation and interpretation [2, 7, 8]. Previous work has been made on databases of small images extracted from medium-resolution sensors. Seidel et al. [5] have experimented a visual-oriented query method on a small test image archive, containing 484 windows extracted from Landsat TM images. Schröder et al. [3] described an intuitive method for semantic labelling of image content suited for query by image content, tested on the same image archive. Schröder [8] and Schröder et al. [4] used a stochastic representation of image content for interactive learning, within a database of about a thousand 1024×1024 Landsat TM scenes – but queries were made by marking training areas. Support Vector Machines were combined with active relevance feedback in [9], and successfully tested on a database of small SPOT images. Other work [1, 6] focused on managing large databases of full remote sensing scenes. Very few works describe the utilisation of content-based image retrieval techniques for the interpretation of a single satellite scene, let alone change detection.

We present an original utilisation and improvement of a CBIR system for the analysis of remote sensing images. In the PicSOM image database browsing system [10], several thousands of images are mapped onto Self-Organising Maps (SOMs) [11], through the extraction of image descriptors including textural and color features. After the SOMs are trained, the user can visually query the database and the system automatically finds images similar to those selected. This approach has been successfully applied to databases of conventional images [12, 13]. Our work aims at using the potential of this neurally-motivated CBIR system for detecting man-made structures, or changes between two or more satellite images, with a special interest in changes involving human activity.

The key idea of our study is to artificially create an "image database" from each satellite image to be analysed, by clipping it into thousands of small images, or *imagelets*. PicSOM can be trained on that virtual database, then queried for finding objects of interest. We extended PicSOM system with features adapted to man-made structures detection in high-resolution optical satellite images. Fusion of panchromatic and multispectral information was done naturally within PicSOM, in which several SOMs are trained in parallel (one per feature). Evaluation of the methods were provided for man-made

structure detection and change detection, using partially labelled datasets. Potential applications of this work are high-resolution satellite image annotation, or monitoring of sensitive areas for undeclared human activity, both in an interactive way.

2. DATA AND PRE-PROCESSING

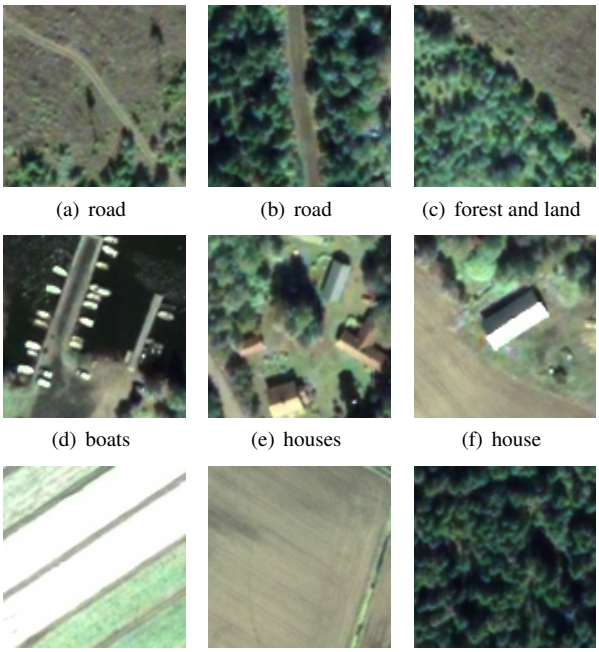
2.1. Satellite imagery

Fig. 1. True-color pan-sharpened QuickBird study scene (2005)

Two QuickBird scenes were acquired in the beginning of September 2002 and in mid June 2005, covering a same coastal area in Finland (Fig. 1). QuickBird images have four spectral channels with a 2.4 m ground resolution – blue ($450-520$ nm), green ($520-600$ nm), red ($630-690$ nm) and near-infrared NIR ($760-900$ nm) – and a panchromatic channel ($450-900$ nm) with ground resolution of 0.6 m. Both images were remarkably cloud-free, while the sea was quite wavy in the 2005 scene.

2.2. Database preparation

A study area of size 4×4 km was extracted from both scenes. PicSOM image retrieval system typically requires several thousands of images in a database, in order to produce relevant indexing. Each image was thus cut into $71 \times 71 = 5041$ non-overlapping small images or *imagelets*, of size 100×100 pixels for panchromatic data and 25×25 pixels for multispectral data. By this operation, the amount of contents in each image is reduced, from many classes in the study scene (bare soil, buildings, forest...), to only a few in each imagelet (Fig. 2).



(a) road (b) road (c) forest and land

(d) boats (e) houses (f) house

(g) agricultural field (h) arable land (i) forest

Fig. 2. Samples of imagelets automatically extracted from the 2005 study area.

The 2002 study area was semi-automatically labelled into seven classes – {*agricultural field, arable land, buildings, clearcuts, forest, roads, water*} –, assigning multiple labels to each imagelet. Buildings were manually labelled in the 2005 imagelets, to allow later quantitative evaluation of the methods.

3. METHODS

The PicSOM system used in this study has originally been developed for content-based image retrieval (CBIR) research [12, 13]. It is based on using the Self-Organising Map (SOM) [11] as an efficient indexing structure for the images. In PicSOM, multiple SOMs are used in parallel, each created with different low-level visual features. We show how this same technique might also be applied in the semi-automated, interactive analysis of satellite images.

3.1. Self-Organising Maps

The Self-Organising Map (SOM) [11] is a neurally-motivated unsupervised learning technique, forming a nonlinear mapping of a high-dimensional input space to a typically two-dimensional grid of neural units. During SOM training, the *model vectors* in its neurons get values

which form a topology-preserving mapping: neighboring vectors in the input space are mapped into nearby units in the SOM grid. Patterns mutually similar in respect to a feature are closely located on the SOM surface. Training is initialised with random values of model vectors $\mathbf{m}_i$ for each map unit i. For each input sample $\mathbf{x}(t)$, the "winner" or *best-matching* map unit (BMU) $c(\mathbf{x})$ is identified on the map by the condition

$$\forall i: \quad \|\mathbf{x}(t) - \mathbf{m}_{c(\mathbf{x})}(t)\| \leq \|\mathbf{x}(t) - \mathbf{m}_i(t)\| \ , \qquad (1)$$

where $\|\cdot\|$ is commonly the Euclidean metric. After finding the BMU, a subset of the model vectors constituting a neighborhood centered around node $c(\mathbf{x})$ are updated as

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + h(t; c(\mathbf{x}), i)(\mathbf{x}(t) - \mathbf{m}_i(t)) \ . \quad (2)$$

with $h(t; c(\mathbf{x}), i)$ a decreasing "neighborhood function" of the distance between the i-th and $c(\mathbf{x})$-th nodes on the map grid. Training is iterated over the available samples, and $h(t; c(\mathbf{x}), i)$ is allowed to decrease in time to guarantee convergence of prototype vectors $\mathbf{m}_i$. After training, all input samples $\mathbf{x}$ are once more mapped to the SOM, each in its BMU. Every SOM unit is then assigned a *visual label* from the imagelet whose feature vector was the nearest to the model vector.

3.2. PicSOM for content-based image retrieval

The PicSOM system [10] has originally been developed for content-based image retrieval (CBIR) research [12, 14]. It implements two essential CBIR techniques, query by examples (QBE) and relevance feedback. These methods can be used for iterative retrieval of any type of visual or non-visual content.

In iterative QBE, the system presents in a visual interface some images to the user, who then marks a subset of them as relevant to the query. This relevance information is fed back to the system, which seeks more similar images and returns them in the next query round. In PicSOM, multiple SOMs are used in parallel, each created with a different low-level visual feature. The different SOMs and their underlying feature extraction schemes impose different similarity functions on the images, allowing PicSOM to adapt to different retrieval tasks.

Relevance feedback has been implemented by using the parallel SOMs. Each image presented in PicSOM is graded by the user as either relevant or non-relevant. All these relevance grades are then projected to the BMUs of the graded images on all SOM surfaces. Maps where there are many relevant images mapped in same or nearby SOM units agree well with the user's conception on the relevance and semantic similarity of the images.

The relevance information placed in the SOM units is spread also to the neighboring units. Each image is given a total qualification value obtained as a sum of the qualification values from its BMUs from the different feature SOM surfaces. Those yet unseen images which have the highest qualification values will then be shown to the user on the next query round. In PicSOM, features that fail to coincide with the user's conceptions always produce lower qualification values than those descriptors that match the user's expectations. More can be found in [15].

Fig. 3 displays a SOM created from the texture feature calculated from the imagelets of Fig. 1. The water regions are mapped in two separate areas due to the different textures of the calm and wavy water surfaces. This shows how PicSOM organises imagelets in the database according to a specific feature.

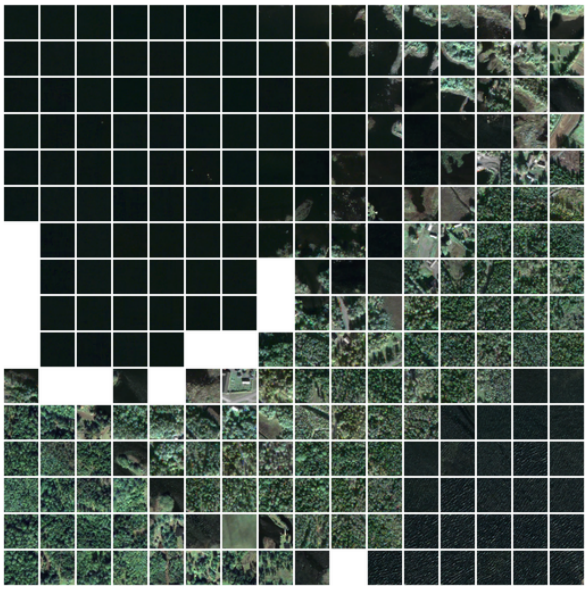


Fig. 3. Organisation of the imagelets by their texture content on a 16×16 SOM surface.

3.3. Features

Features used in CBIR usually describe generic image properties, like color distribution, texture or shapes [9]. Color moments, RGB average and texture features are part of PicSOM [10], and were used in a preliminary study [16]. Three features were added for the specific purpose of detecting man-made structures or changes in satellite imagery:

> xy**-coordinates** indicate the spatial location of an imagelet in the original scene as row/column indexes – independently of the year, image content or data source.
>
> **NDVI:** a 100-bin histogram of Normalised Difference Vegetation Index computed on imagelets.
>
> **edges histogram** Pattern directionality [17] is based on the histogram of gradient magnitude against the gradient angle. We modified that feature so that the histogram is centered around the direction of strongest edges.

Fig. 4 shows imagelets from the 2002 image, with their NDVI and edges histograms. The presence of a building generates a typical signature on the edges histogram.

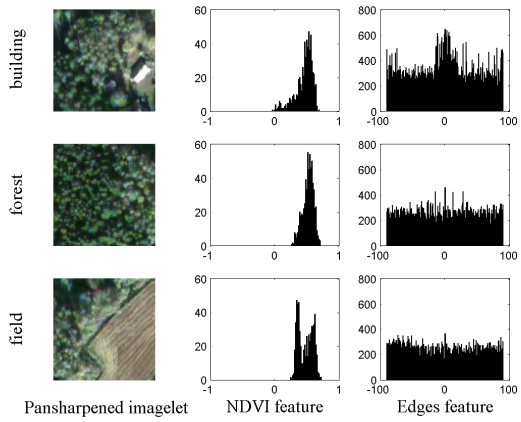


Fig. 4. Three sample imagelets from 2002 representative of classes building, forest, field, and their features.

Each feature vector was used 100 times in training (Eqs. (1) and (2)). The map sizes were set to 64×64 units for the visual features SOMs, and 71×71 for the coordinate SOM. Therefore, there were on the average $5041/4096 \approx 1.23$ imagelets mapped in each map unit of the visual SOMs, and exactly one image location on the coordinate map. Color moment and edges features are good candidates for building detection, as their distribution is localised for class *building* - [15].

3.4. Detection of man-made structures with CBIR

In our study, we have used the PicSOM CBIR system to interactively find imagelets containing man-made objects such as buildings or roads. The system first displays a random selection of imagelets in a web browser. The user then selects all imagelets containing man-made objects – or anything else but water and forest – and sends this information back to the system by pressing the 'Continue query' button. In the forthcoming query rounds, the user can then focus the query more precisely to more specific semantic targets, such as buildings, roads or clearcuts.

Fig. 5 shows the user interface of the system in the middle of an interactive query session. The user has selected some man-made objects shown in the middle of the browser window. In the top part, the distribution of those imagelets are shown with red colors on the four different SOMs. In the bottom of the interface, some of the new imagelets returned by the system are shown to the user.

PicSOM system can also be used to perform automatic detection of man-made structures. The qualification value assigned to each imagelet by the PicSOM system is a discrimination value, which indicates the likeliness that the specific imagelet belongs to that semantic class

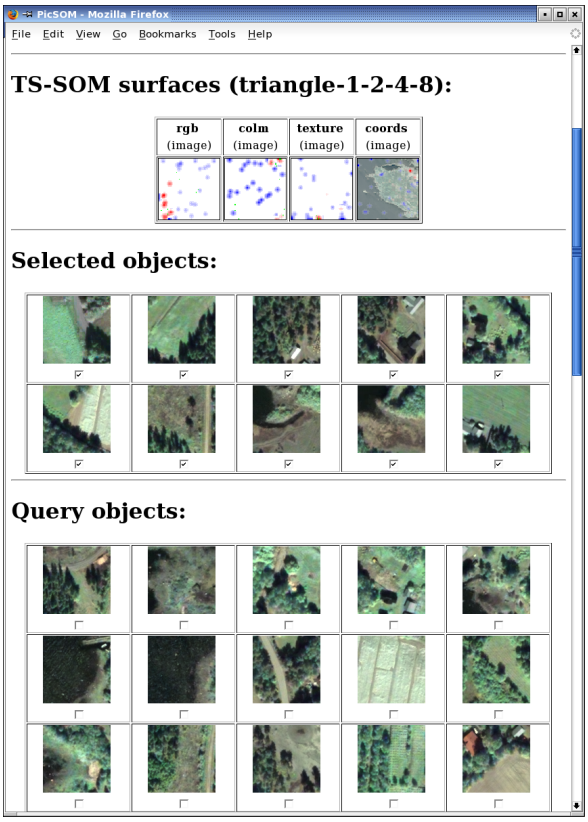


Fig. 5. The web user interface of the PicSOM system in an interactive query for man-made objects.

(label) [15]. Imagelets can be sorted by decreasing order of similarity to a given class, and a threshold can then be set to retrieve the most similar imagelets to that semantic class.

3.5. Content-based detection of changes

We devised a method for finding pairs of imagelets, one from the year 2002 and the other from 2005, which differed the most in the sense of some of the extracted features. Only the true changes in the imagelet's content would then give rise to such a striking change in the feature vector's value that its projection on the SOM surface is moved to a substantially different location. The substantiality of the change can therefore be measured as the distance between the best matching units (BMUs) of the different years' feature vectors on a same SOM.

3.5.1. Supervised change detection

Assuming that the system produces larger discrimination values for imagelets that portray man-made structures than those that do not, then a temporal increase in the discrimination value indicates that a new man-made structure has probably appeared. All imagelet pairs can

be sorted by decreasing order of change in this discrimination value. This change detection is supervised in the sense that one needs to have labeled training data in order to create the class models [15].

3.5.2. Unsupervised change detection

The dissimilarity between imagelets was again defined solely on the SOMs. Imagelet pairs were ordered by descending pair-wise BMUs distance on a given feature SOM – the higher the distance, the more substantial change in content occurred. A fixed number of imagelet pairs, set to 70 in this study, were then regarded as the locations where the most substantial changes had taken place. Several feature SOMs can be used simultaneously, in which case the pair-wise BMUs distances on different SOMs are normalised then combined [15].

4. RESULTS AND DISCUSSION

4.1. PicSOM for detection of buildings

PicSOM was trained on the 5041 imagelets of 2002, and tested on imagelets of 2005. Those sets included, respectively, 244 and 266 imagelets with buildings. Two-fold cross-validation on the training set was used with sequential forward selection to select those features maximising the area under the Receiver Operating Characteristic (ROC) curve [18]. NDVI, edges and color moment gave the highest area under ROC curve, $auc = 0.94$ (Fig. 6).

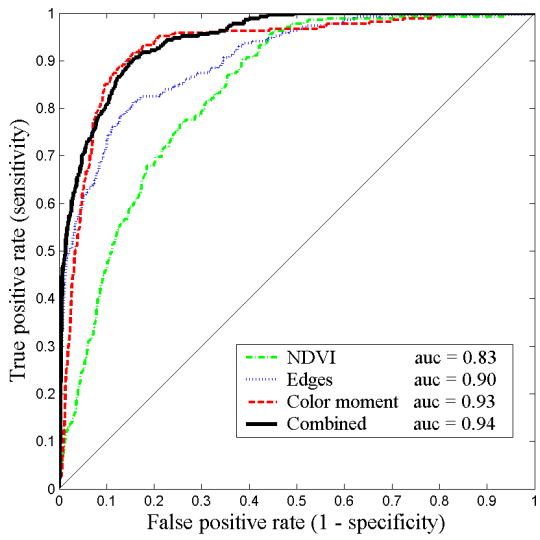


Fig. 6. ROC curves of different features for building detection in 2005 set.

PicSOM was also used interactively. This time the feature SOMs were trained on all imagelets from the two study scenes. A validation scene was selected in the 2005 QuickBird image, then cut into $60 \times 90 = 5400$ imagelets. Experiments were carried out by four different persons, each doing 10 successive queries. PicSOM returned a comfortable majority of relevant images (i.e. containing buildings) in the validation set, already after three query rounds. Similar results were achieved when visually selecting clearcuts or arable land as target. This already shows the ability of PicSOM to perform supervised, general-purpose and interactive satellite image annotation, by visual and intuitive querying.

4.2. PicSOM for change detection

4.2.1. Supervised change detection

The labelled database contained 40 imagelet pairs where buildings appeared between 2002 and 2005. The best detection accuracy was obtained by using the edges feature alone, with $auc = 0.87$. Other features or feature combinations performed rather poorly in this task, with an auc at best close to 0.6. Setting a detection threshold at 30 imagelet pairs returned 11 true positives changes, and 19 false positives. These 30 locations are shown over the test area in Fig. 7. Darker red colors indicate that many adjacent imagelets have changed. False positives appeared in the vicinity of built-up areas.

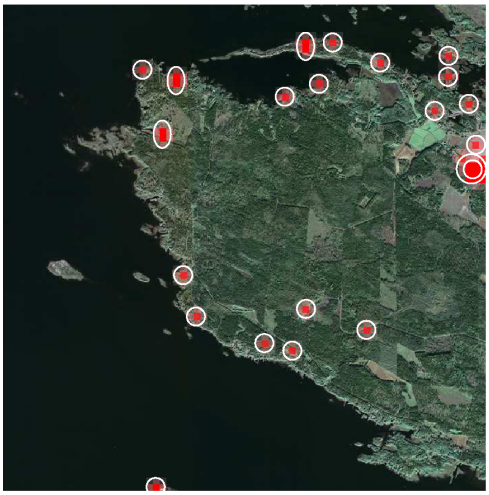


Fig. 7. 30 most prominent 2002–2005 changes in the edges SOM

4.2.2. Unsupervised change detection

We evaluated our unsupervised change detection method with the ground-truth available for buildings in both years. The best feature combination was average RGB and edges features ($auc = 0.63$). The result is quite reasonable as the procedure detects all changes, not only changes in buildings. Therefore, we would need a ground truth that includes all changes – not only in buildings – to demonstrate all the potential of the method.

4.2.3. Discussion on change detection

Pixel-based change detection in very high resolution imagery is a challenging task, limited by the requirement of pixel or sub-pixel accuracy registration. A clear advantage of the decomposition in imagelets in the context of change detection, is that it relaxes this constraint. Results suggest that the slight misregistration between the 2002 and 2005 scenes did not affect much the performance of PicSOM for change detection.

Imagelet-based structure detection does not provide direct delineation of objects of interest (contrary to pixel-based methods), but it can highlight in a full scene locations with potentially interesting structures or contents. Similar methods could also be applied to SAR imagery, with appropriate features descriptors.

A way to refine the change detection would be to provide two content targets to PicSOM : a content from which the change occurs (*earlier target*), and a content to which the change occurs (*later target*). This would allow an intuitive and interactive definition by the user of changes of interest – e.g. by selecting imagelets containing forest as earlier target, and buildings as later target, the system would detect newly constructed buildings in forest areas.

The 100×100 pixels imagelets, extracted from QuickBird images used in this study, seemed to provide a trade-off between the two undesirable situations. Luckily and surprisingly, not too many buildings in the study scene were split into two or more imagelets. In order to reduce the consequences of "cutting" an object of interest into several non-overlapping imagelets (namely, generating "artificial" objects on the borders of imagelets), overlapping imagelets could be used. The size of imagelets could also be tuned in an operative system.

5. APPLICATION FOR MONITORING OF NUCLEAR WASTE REPOSITORY SITE

A pilot system was developed for monitoring of a geological repository site of spent nuclear fuel. The system user is STUK, the Radiation and Nuclear Safety Authority of Finland. The emphasis in the design of the system was on the change detection in natural environment due to man-made constructions in the infrastructure.

The goal was to monitor activities concerning buildings, roads and quarries and their environmental impacts at the repository site and in the surroundings, e.g. in vegetation cover. The nuclear waste disposal operations will last from now on to the final closure of the repository – this means a long-term commitment to the monitoring activities for about one hundred years.

5.1. Spatial and temporal coverage of input data

Although no considerable changes in the natural environment are expected in the short run, the long-term alterations in the vegetation cover are still possibly caused by natural growth, air constituents and eventual descend of the ground-water level. Change monitoring based on optical satellite data will be the most suitable technique for long-term surveillance on annual basis. The Geological Repository Safeguards Expert Group supporting the IAEA has considered a 10km radius to be reasonable for monitoring [19]. In general this is met in satellite monitoring where the typical swath width is tens or even one hundred kilometers. Different types of digital satellite imagery with a variety of ground resolutions can be used.

5.2. Image analysis

Since the required monitoring time is very long (to the indefinite future), it is clear that regular monitoring should be as automatic as possible. However, the techniques that were applied were semi-automatic and interactive, since fully automatic methods are not considered to be reliable enough for the operative system. There should be always a possibility for manual image analysis because there can be circumstances where automatic image interpretation methods do not work properly, as e.g. in springtime when partly bare ground has been exposed.

One of the semi-automatic algorithm tested for detecting the changes in high resolution images was the technique based on PicSOM [15, 16]. So far the methods have been successfully applied to very high resolution optical images [15], but could be used as well with SAR images with appropriate feature descriptors. The flexibility of the system can also allow fusion of clues coming from different data sources, e.g optical and SAR images. Future work will investigate these possibilities.

5.3. Delivery of results

The final products (after being produced "offline") are delivered to the user "online" through a web map service. In the pilot system a password-protected map service was implemented using the ArcIMS software, which enabled provision of general GIS functionality to the user (e.g. pan, zoom, and attribute data). In the future, also the mobile service to PDA's or mobile phones shall be considered an optional delivery channel. All the delivery channels have to be reliable, secure and authorised to be available to the authorities only. ArcIMS performs user authentication for map services, allowing the operator to define which users have access to image products.

An operating prototype system was developed to the extent that STUK could take it in test use. The pilot version of the system is a processing chain of separate modules and software packages, which an expert operator runs.

5.4. System perspective

The comprehensive environment of the operative repository site monitoring system is illustrated in Fig. 8.

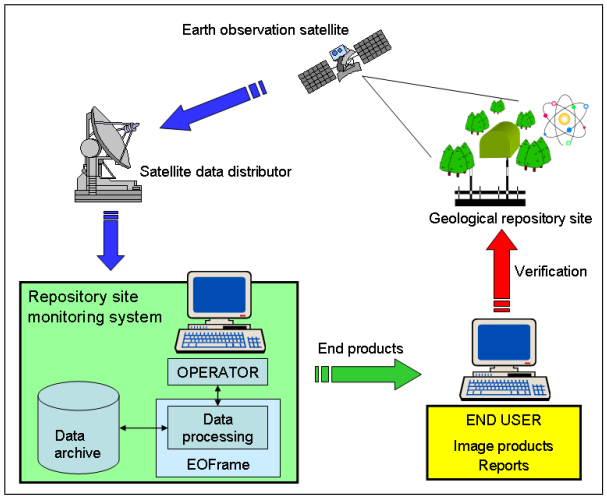


Fig. 8. Comprehensive block diagram of the nuclear repository monitoring system

The satellite imagery covering the target area is provided regularly. Repository site monitoring system is used by the operator for processing the imagery into a form that is suitable for the user. Apart from the actual data processing modules in the specified processing chain, the system includes a data management facility for the system operator who processes the intermediate and end products, e.g. thematic maps, enhanced images and reports. The product delivery tools are the web server, the mail server, and the file server (or FTP). The user may take verification actions on the site based on the end products which can be accessed via appropriate methods e.g. web browser, PDA, mobile phone (MMS).

The phases of the repository site monitoring system in a general level are presented in Fig. 9. The complete system has three principal elements: the baseline (in blue shapes), routine monitoring (in green shapes), and alarm survey. The routine monitoring part includes semi-automatic analysis of the images over the study site.

All the pre-processing of the optical and SAR images was carried out using the Data Pre-processing Module of the EOFame, a common framework for processing Earth Observation data developed within the ENVIMON project [20]. It includes all the tasks from data unpacking and radiometric calibrations to geometric corrections. The basic principle of the Data Pre-processing in the EOFrame is that only the unpacking module is sensor dependent. Radiometric calibration and geometric correction modules are generic, and they handle any kind of data as long as they are in correct format.

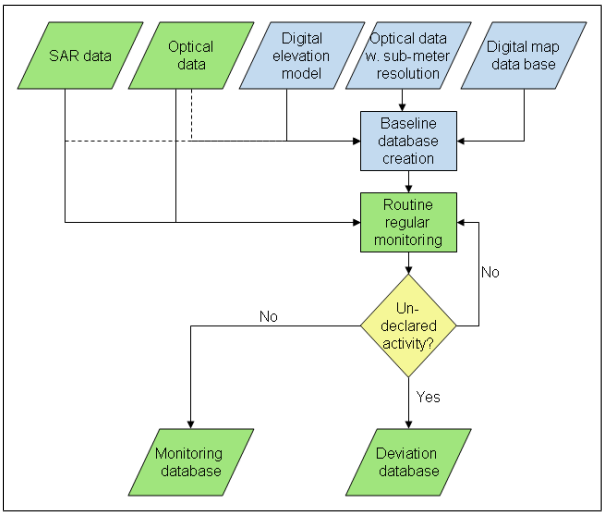


Fig. 9. Phases of the repository site monitoring in a general level

5.5. Potential benefit of Content-Based Image Retrieval for long-term monitoring

A content-based image retrieval system like PicSOM demands a great number of images in the database in order to produce relevant indexing. This imposed the choice of dividing each image into several thousand imagelets, when two images were processed. In the long run, with more full scenes acquired, imagelet indexing will become more relevant. SOMs that have been trained using previous images can be used in the analysis of new imagery : the results of interactive retrieval sessions can be stored as non-parametric target class models for future offline analysis of similar semantic contents. This step could constitute the baseline for a monitoring application, i.e. novelty or change detection with two or more images.

On an interactive point of view, such a system could point out locations in the recently acquired full image where potentially interesting structures or patterns may be located – e.g. types of targets defined visually by the user that may have appeared or disappeared. Those locations could then be checked by an operator, and marked either as relevant or irrelevant, thus constantly improving and interactively refining the definition of targets of interest. PicSOM, seen as a machine learning system, can improve its "implicit knowledge" of the structures or ongoing changes by such feedback.

6. CONCLUSIONS

We have presented how a content-based image retrieval system, PicSOM, can be used with remote sensing images for tasks like segmentation of man-made structures or clearcuts, as well as change detection. The approach relies on the decomposition of a satellite image into several thousands small images or imagelets, to generate an

image database from which the user can query, visually and intuitively. The same framework allows for detection of a specific content of interest (e.g. buildings), as well as change detection. Experimental results suggest the approach is suitable for high resolution optical images. The versatility of PicSOM will allow several applications to be embedded in a same operative and interactive system, only to be differentiated by the type of query. One of the many possible applications of this work is long term monitoring of human activity around strategic sites.

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