Multitemporal Analysis of Floods and Tsunami Effects: annotations and quantitative analysis

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***Abstract*—This paper addresses the problem of multitemporal analysis of an available TerraSAR-X data time series covering the Sendai region in order to assess flood extent and damages caused by Tohuku-oki tsunami. Over the last decade the use of Earth Observation satellites to support disaster and emergency relief has considerably grown. In order to fully exploit highresolution satellite images, a method based on patches (each image is divided into non-overlapping tiles) is proposed to extract relevant contextual information. The local features of each patch act as a compact content descriptor. Further on, considering the available descriptors, the next step is to cluster the data in order to find similar semantic classes. The SVM classifier implements the concept of query by example using image content. The results include well-defined semantic classes, derived through semiautomatic methods thus developing an effective approach to the multitemporal analysis.**

I. Introduction

The purpose of this paper it to present a new approach that completes the classic Rapid Mapping products used to evaluate the impact of a disaster on a region, considering multitemporal high resolution satellite images. Rapid Mapping services provide information support during response and immediate post-response by delivering products emphasizing the extent and impact of the event, by event understanding any type of natural or man made disaster. Rapid Mapping products are ready to use maps of the event revealing the disaster extent, scale and possible impact with overlaid cartographic information. The analysis of remotely sensed imagery proposed in the following is based on TerraSAR-X (TSX) post seismic satellite time series of 3-month duration covering the area around Sendai in ascending and descending orbits in stripmap mode and on a few TSX scenes acquired before the earthquake, between 2008 and 2011.

II. Earthquake and tsunami information

The 11 March 2011 earthquake in northern Japan and the tsunami that followed left thousands of persons dead or missing. The epicenter was at 129 km away from Sendai, the largest city in the Northeast area of Japan, at 38.297N, 142.372S. The destructive tsunami, produced by the earthquake hit the coastline several minutes after the earthquake causing huge casualties, damages and the crisis at the Fukushima Daiichi nuclear plant. On March 12 the Sendai region was partially clouded so that only the use of microwave data SAR data, capable to penetrate clouds, allows a detailed and complete evaluation of the region. SAR systems have the capability to work in cloudy conditions, no matter if it is day or night, thus becoming a powerful tool to monitor and assess disasters. Multiple space agencies openly provided data for scientific use. The imagery was provided via ESAs Virtual Archive, a cloud-based cyberinfrastructure that ensures rapid online access anywhere in the world.

From the available time series two radiometrically enhanced TSX images acquired before (20.10.2010) and after (12.03.2011) the tsunami were used (Fig.1). Each TXS image is accompanied by a TSX XML file which describes in detail the product type and properties relative to acquisition, from which we summarize: horizontal polarization, descending orbit, right looking, 5.77 ground range resolution, 5.75 azimuth resolution, incidence angle 36.

III. Multitemporal analysis scenario

Knowledge discovery from Earth Observation (EO) images implies mapping low level descriptors extracted from the image into semantic classes in order to provide an interactive method for effective image information mining. In the frame of information theory one can consider a communication channel between remote sensing imagery and the user who receives the existing information in the data sources, coded. This channel

Fig. 1. Overlay on Google Earth of the two TSX images.

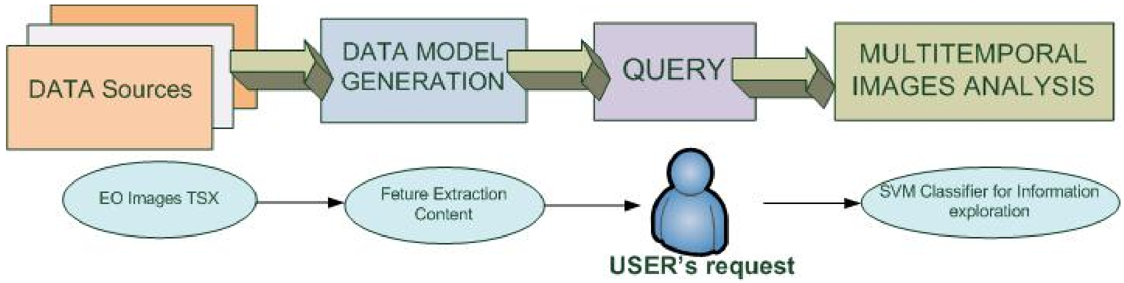


Fig. 2. Knowledge discovery components for EO images.

may involve three components - Data Source Model, Query and Data Mining, as depicted in Fig.2

Data sources are EO images, in this case TerraSAR-X basic products, to be described in what follows. The Data Source Model component regards image content analysis considering as input TSX images to generate the output as a vector of image content descriptors. These descriptors are actually texture features obtained through a feature extraction process, the images spectral properties, dictionary elements as a result of compression techniques and metadata [1]. The Query componenet involve the user and takes into account a query based example, an operation integrated in the last component, in fact a Support Vector Machine classifier able to group descriptors into relevant semantic classes [2]. The classifier supports multitemporal image analysis and interactive mapping.

The Data annotations stage considers dataset description, data preparation and data classification in order to perform user annotations. For each TSX product the image is tiled into non overlapping patches (14700 items) using the patch tiling algorithm described in [3]. The size of the patch was chosen considering image resolution and pixel spacing and it is 100 x 100 pixels. These dimensions ensure that the extracted features capture the local properties of a region (patch) rather than the global properties of the image.

At the next level these patches are converted into local features [5] to be further used as content descriptors, relevant to characterize image structures. The obtained feature vectors are further stored in a database. The envisaged algorithms for feature extraction includes: Grey Level Co-occurence Matrix (GLCM), the Non Linear Short Time Fourier Transform (NSTF), the Gabor Filters (GAFS) and the Quadrature Mirror Filters (QMSF). Inputs for these algorithms are GeoTiff data (byte, unsigned integer, and float).

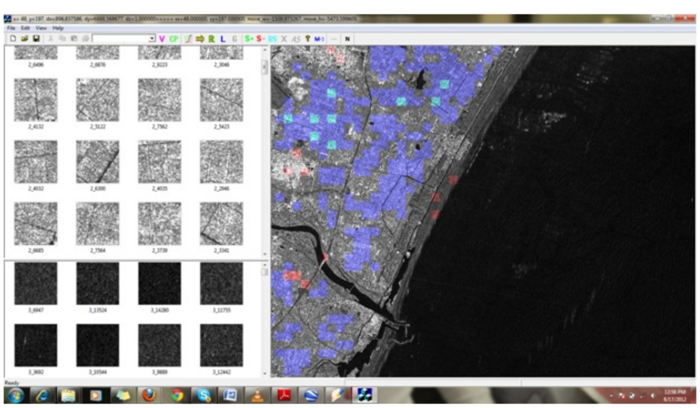


Fig. 3. Instant of the SVM classifier highlighting in blue the semantic label "agriculture" obtained in one iteration by giving positive (in green) and negative examples (in red) directly on the image. In the upper left corner of the screen all the patches similar with the given examples "agriculture" are revealed while in the lower left corner of the screen the similar negative example (like "ocean") are presented.

Feature extraction is a key step in image content description. For this purpose the "Bag of Words " algorithm, shortly detailed in [6] was used. Recently introduced in the remote sensing community the BOW model is mainly applied to image classification. This method comes from text analysis wherein a document is represented by word frequencies irrespective of their order.

Further, these frequencies are used to perform document classification. Identifying the visual equivalent of a word is therefore necessary before the method can be applied to images. This is usually done by producing local invariant features. Local features are extracted from the local neighborhood around SIFT points or densely sampled patches. To construct the vocabulary, a clustering, usually K-means, is performed to find clusters. Cluster centers are used as vocabulary for computing word occurrence histogram. After vocabulary generation, each local feature is assigned usually to the closest cluster and thus the image can be represented as the word occurrence histogram. Considering the extracted descriptors the next step is clustering which aims to dissociate recognized classes. Further on, an active learning stage is mandatory in order to label the classes. To each of the established classes one can add a semantic label.

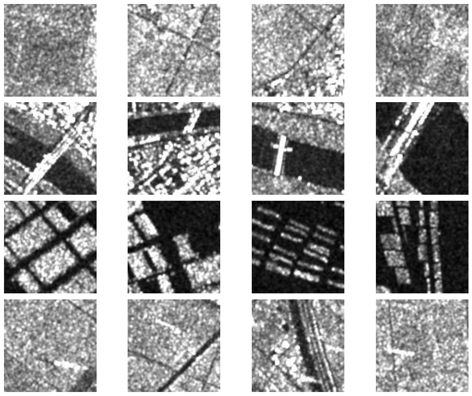
A system that implements the concept of query by example and the semantic definition by learning methods is a Search Engine whose main core is a Support Vector Machine (SVM) classifier. This tool relies on:

1) feature extraction methods providing the most relevant descriptors of the images
2) SVM as classifier grouping the image descriptors into generic classes (without semantics)
3) relevance feedback interacting with the end user.

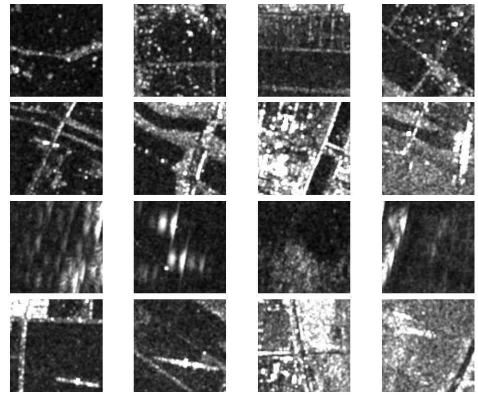
A description of the search engine based on SVM is given in [1]. The methodology consists in performing an iterative annotation of TSX images patches using the Support Vector Machine with a relevance feedback supplemented by the human expertise. Before using the SVM classifier as a search engine to assign semantic labels to patches, the

TABLE I. SEMANTIC CATEGORIES EXTRACTED FROM A)TSX PRODUCT 20.10.2010 (BEFORE) AND B)TSX PRODUCT 12.03.2011(AFTER)

Agriculture
Bridges
Aquaculture
HV Poles



Flooded areas
Bridges
Debris
HV Poles



extracted features need to be normalized. Considering up to ten iterations, the SVM classifier is able to almost completely retrieve all the similar patches belonging to the same semantic label, in the example presented in Fig. 3, that is ”agriculture”.

Typical semantic classes extracted from the two TSX images (before and after the tsunami) are presented in Table I. Following several search scenarios and using the classifier, the user is able to retrieve: ”human made structures”, ”bridges”, high voltage poles”, ”aquaculture”, etc. Before the tsunami one can observe clearly delimited structures relatively easy to delineate like urban areas, agriculture regions and even aquaculture of brown seaweed. After the event some of the previously identified classes turned into ”flooded areas”.

IV. QUERY STAGE

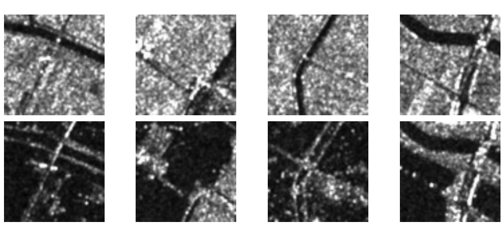
In what follows, some examples of queries using the image content are presented. These queries are the basics for the post disaster evaluation, considering several scenarios like:

A. Assessment of the transportation infrastructures, high risk of broken roads caused by damaged bridges

Query by semantic label ”bridges” in the image before the tsunami jointly with the semantic label ”flooded area” in the image after the tsunami, followed also by a query by ”bridges” in the second image to assess the results (Table II).

TABLE II. PATCHES DEFINED BY THE SEMANTIC LABEL ”BRIDGES”, BEFORE AND AFTER THE EVENT

Bridges before
Bridges after

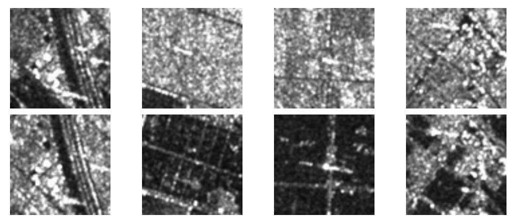


B. Possible energy loss due to the damaged high voltage poles, if any.

One of the categories highlighted in the annotation phase is that containing the locations of high voltage poles. It is possible to determine if some of these poles were damaged querying to see if there are any patches defined by those semantic labels. Part of the results of a query by ”high voltage poles” and ”flooded area” are presented below, in Table III.

TABLE III. PATCHES DEFINED BY THE SEMANTIC LABEL ”HIGH VOLTAGE POLES”, BEFORE AND AFTER THE EVENT

HV poles before
HV poles after

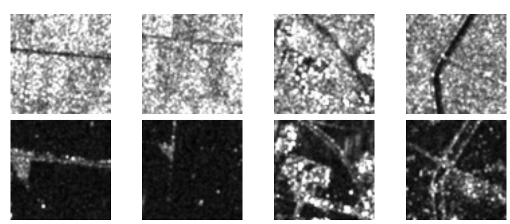


C. Assessment of agriculture areas, damaged crops and estimation of losses.

In order to assess the damage caused by the tsunami to agricultural fields, the first query has been done considering the semantic label ”agriculture”, followed by a second one, considering ”flooded areas”. Some of the results are presented in Table IV, revealing the same areas, completely damaged.

TABLE IV. PATCHES DEFINED BY THE SEMANTIC LABEL ”AGRICULTURE”, BEFORE THE EVENT, TURNING INTO ”FLOODED AREAS” AFTER THE DISASTER

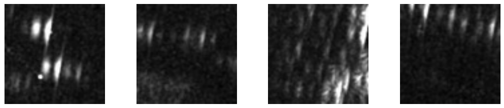
Agriculture
Flooded areas



D. Debris detection

Because of the large potential area of debris drift in the ocean, it is critical to consider debris detection. Environmental organizations collaborates with the state and with local partners interested to detect debris and its movement in order to estimate potential impact along the coastline. In Table V some of the patches identified by processsing the image taken after tsunami are presented.

TABLE V. PATCHES DEFINED BY THE SEMANTIC LABEL "DEBRIS", AFTER THE EVENT



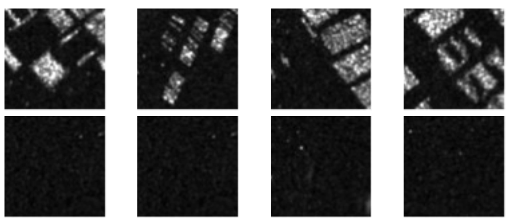
Debris

E. Assessment of aquaculture areas.

Japan has long been recognized as a leader in aquaculture, Matushima representing one of the most important culture areas in Myagi prefecture. Over the years, this region was converted from oyster culture to seaweed culture. Prior to tsunami one can delimitate in this region large areas of aquaculture. After the disaster none of this areas remained unspoiled, everything becoming ocean.

TABLE VI. PATCHES DEFINED BY THE SEMANTIC LABEL "AQUACULTURE", BEFORE THE EVENT, TURNING INTO "OCEAN" AFTER THE DISASTER

Brown Seaweed



Ocean

V. CONCLUSIONS

The scenarios described in Section IV consider knowledge discovery from pre and post disaster EO images by mapping the extracted primitive features into semantic classes and symbolic representations like: "urban areas", "agriculture", "mountains", "bridges", "aquaculture", "high voltage pylons", "flooded areas", etc. The results of the query include well-recognized patches sharing the same semantic label. Thus, it is possible to determine tsunami effects on several levels: assessment of transportation infrastructure post disaster, possible power outages due to the damaged high voltage pylons, flooded urban regions, evaluation of agricultural fields, damaged crops and estimation of losses and so on. In addition, query results can be quantitatively evaluated and further used to estimate the impact that the tsunami had on the Sendai region. Through multitemporal images analysis this kind of approach complements the Rapid Mapping products providing the ability to detect changes using the user's experience and knowledge along the entire process of data mining.

VI. ACKNOWLEDGMENT

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Images provided by courtesy of DLR (German Aerospace Center).

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