

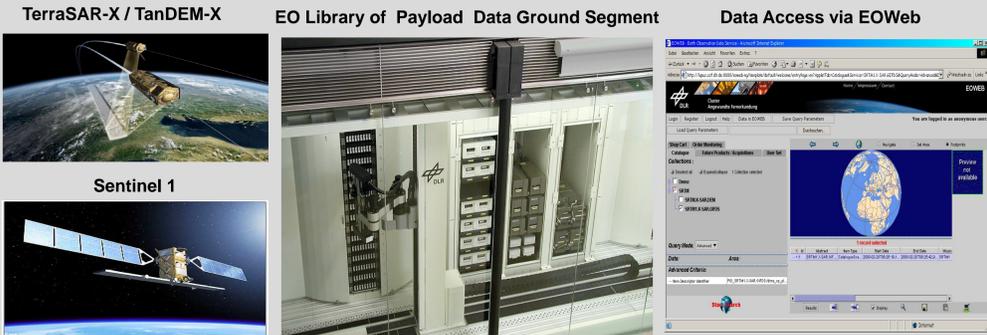
Interactive Clustering for SAR Image Understanding

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Challenge: Exploiting Huge Earth Observation (EO) Data Volumes



The Earth is facing unprecedented climatic, geomorphologic, environmental and anthropogenic changes which require global scale observations and monitoring.

The collected EO data volumes are increasing immensely with a rate of several Terabytes of data a day. With the current EO technologies these figures will be soon amplified, the horizons are beyond Zettabytes of data. The challenge is the exploration of these data and the timely delivery of focused information and knowledge in a simple and understandable format.

As users of EO data well know, image and data repositories are enormous, much too large to be scanned or analyzed thoroughly by humans. Practical approaches to use successfully such data and imagery must necessarily automate the retrieval of relevant images from a large repository.

Motivation:

Browsing and visualizing image collections is a key part in Visual Data Mining (VDM) systems. In such systems, the content of each image (e.g., color, texture, shape) is represented by a high-dimensional feature point. Furthermore, the similarity relationship between images is measured on the basis of the distance between feature points. In VDM, a query image might be loaded into the system and the resulting similar images are visualized as thumbnails in a 2D or 3D display space. For visualization dimensionality reduction is widely used to determine the position of images. However, the images are mostly occluded and much of the display space is not used. Therefore, it is essential to arrange the images in the display space in such a way that: 1) the similar images are positioned close together; 2) the display space is used as efficiently as possible by uniformly distributing the images.

Image Positioning Algorithm:

Let us assume that the initial positions of a set of images $\{I_i\}$ are represented by three dimensional points x_i , where $i = 1:N$, and N states the number of images. The goal is to find the optimal position of each image, y_i . For each image, i , we define asymmetric probabilities, P_{ij} and Q_{ij} , from the initial and optimal positions of images respectively, showing the probability that i is a neighbor of j .

$$P_{ij} = \frac{\exp(-\|x_i - x_j\|^2)}{\sum_{i \neq k} \exp(-\|x_i - x_k\|^2)}$$

$$Q_{ij} = \frac{\exp(-\|y_i - y_j\|^2)}{\sum_{i \neq k} \exp(-\|y_i - y_k\|^2)}$$

$$C_{dis} = \sum_i \sum_j P_{ij} \log \frac{P_{ij}}{Q_{ij}}$$

We assume each image occupies a sphere with radius $r = \max\{w, h\}w$ and h represent the width and height of each image. For each image, a Gaussian $G_i(\mu = Y_i, \sigma = r\sqrt{\frac{R^2}{N+1}})$. The Gaussians of all image positioned are mixed to define a Gaussian mixture model $P(Y)$ with quadratic entropy equal to H .

$$P(Y) = \sum_{i=1}^N G_i(Y; Y_i, \sigma) \quad H = -\log \int P(Y)^2 dy = -\log \left\{ \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N G_i(Y_j; Y_i, \sigma) \right\}$$

In order to have less overlap between images, we need to increase the entropy of $P(Y)$. We have two cost functions such that their combination leads to a single cost function controlled by a parameter.

$$C_{tot} = (1 - \lambda)C_{dis} - \lambda H$$

The minimization of C_{tot} gives rise to an optimal positioning of images. Practically, this minimization can be solved by the gradient descent method, where the gradient of C_{dis} , and H are.

$$\frac{\delta C_{dis}}{\delta Y_i} = 2 \sum_{j=1}^N (Y_i - Y_j)(P_{ij} - Q_{ij} + P_{ji} - Q_{ji})$$

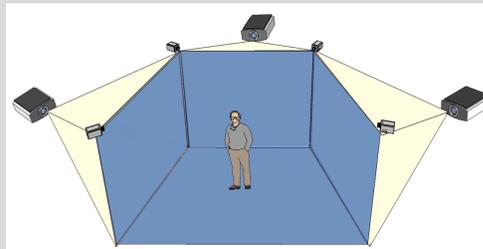
$$\frac{\delta H}{\delta Y_i} = \frac{1}{2\sigma\alpha} \sum_{j=1}^N \{G_j(Y_i; Y_j, 2\sigma) * (Y_i - Y_j)\}$$

where

$$\alpha = \sum_{i=1}^N \sum_{j=1}^N G_j(Y_i; Y_j, 2\sigma)$$

Concepts:

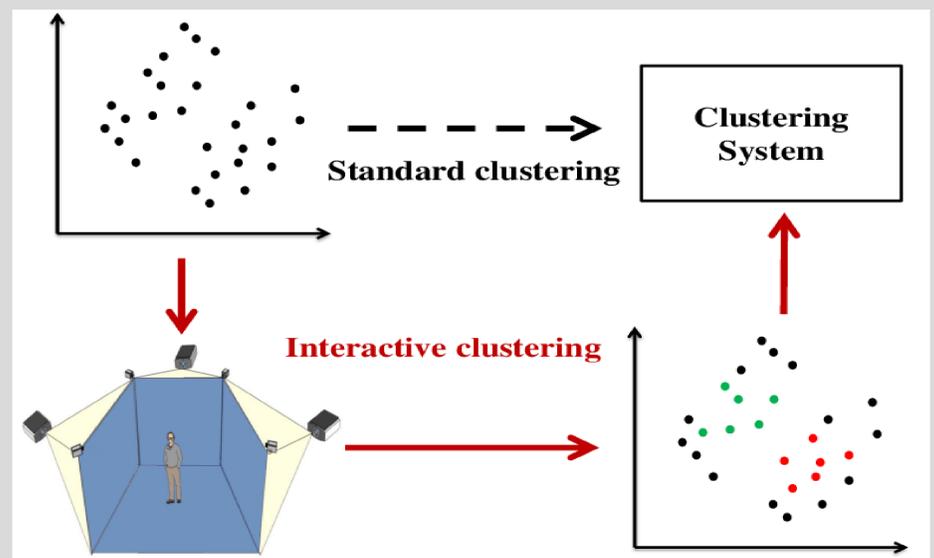
Immersive Visual Data Mining



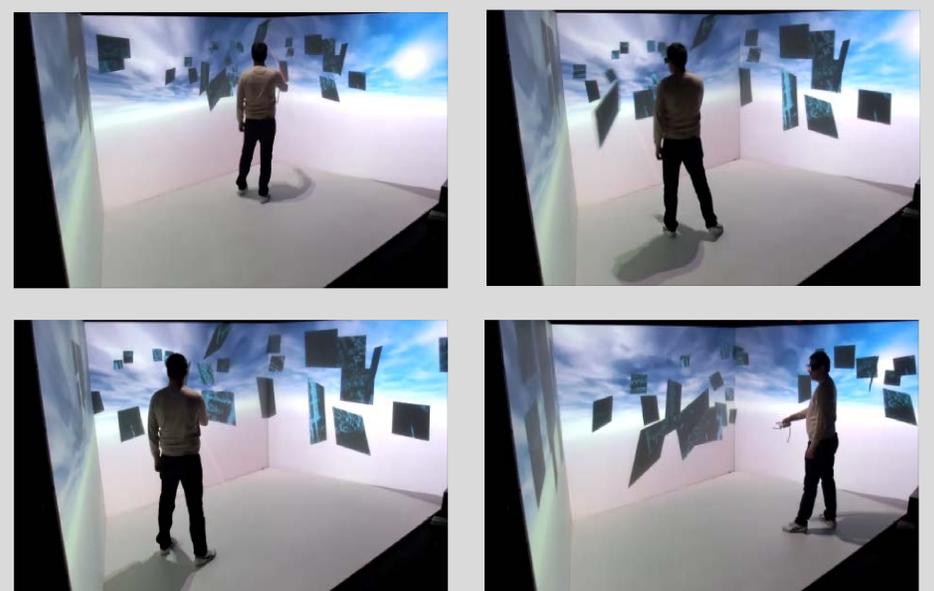
Immersive visual data mining: the SAR data from the DLR EO Digital Library will be processed for **descriptor extraction**, the descriptor space will be analyzed and **projected adaptively in 3D space, visualized in the CAVE**, jointly with **multi-modal rendering of the images** and their content. The analyst, immersed in the CAVE, will be enabled to **interact with the data content** using learning algorithms and navigate, explore and analyze the information in the archive.

We propose an immersive 3D virtual environment for visualization of minimum spanning tree of data points. This environment, the so-called Cave Automatic Virtual Environment (CAVE) is based on Virtual Reality technology and comprises four room-sized walls aligned to form a cube to display the low-dimensional features. This configuration allows users to have a 180 degree horizontal view. The virtual scene is projected onto the walls using two projectors per wall in order to have stereoscopic scenarios. Additionally, a real-time tracking system including six infrared cameras mounted on top of the walls computes the pose (position and orientation) of marked objects (e.g., Wii controller and shuttle glasses) inside the cube.

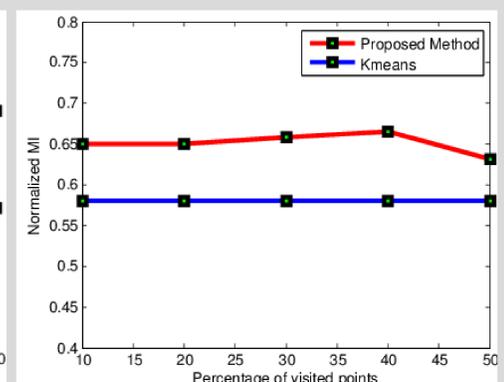
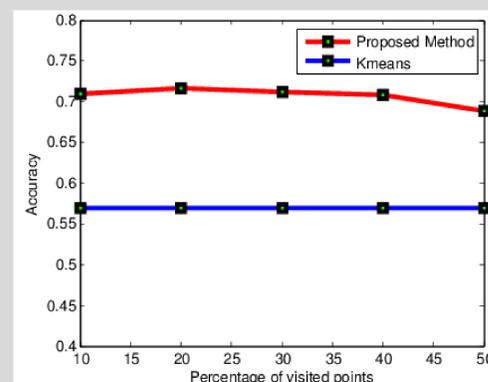
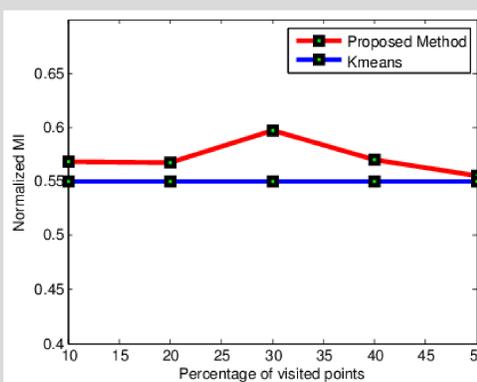
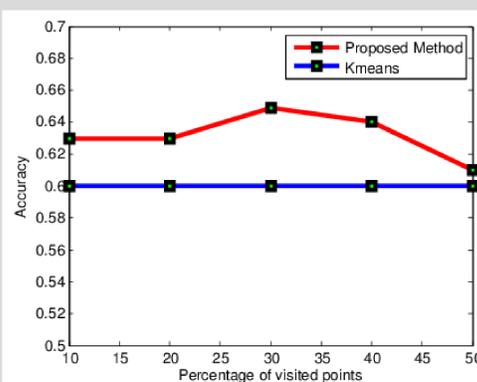
Interactive Clustering:



Cave Automated Virtual Environment (CAVE):



Clustering Results:



Further Details:

- Mohammadreza Babae, Mihai Datcu, Gerhard Rigoll: Assessment of Dimensionality Reduction Based on Communication Channel Model; Application to Immersive Information Visualization. IEEE workshop on large scale Machine Learning.
- Mohammadreza Babae, Gerhard Rigoll, Mihai Datcu: Immersive Interactive Information Mining with Application to Earth Observation Data Retrieval. CD-ARES 2013: 376-386