SPATIOTEMPORAL FILTERING OF MULTI-TEMPORAL IMAGES: APPLICATION ON MODIS SEA SURFACE TEMPERATURE (SST) IMAGERY

Panagiotis Partsinevelos
Technical University of Crete
Department of Mineral Resources Engineering
University Campus
Chania, 73100, Crete, Greece
email: ppartsi@mred.tuc.gr

George Miliaresis
University of Patras
Department of Geology
Geology Department
Rion, 26504, Greece
email: gmiliar@upatras.gr

Abstract

In this paper a series of spatiotemporal (ST) filters are devised in order to retrieve change information from multi-temporal imagery depicting continuous-field data. Based on common spatial filters, derivative filters are extended to include 3-dimensional applicability, while new complex filters are designed to assist information retrieval under various application perspectives. In addition, ST filtering does not concentrate on a single pixel where possible uncertainty resides but is applied upon a pixel group lying inside a defined parallelogram. Hence, weight, parallelogram size and filter shape selection lead to varying information extraction, including merely temporal, abrupt, gradual, directional and user defined spatiotemporal change. ST filtering of multi-temporal imagery results in a new multi-change dataset depicted as a 3-dimensional cloud of points classified in magnitude and/or type. This dataset is further examined to capture and visually convey an overall summarized change behavior. Thus, a self organizing map algorithm is utilized, spreading along the change space and forming a 3-dimensional representative - signature polyline. To demonstrate the applicability of the proposed ST filters, monthly averaged sea surface temperature (SST) Modis images throughout a three year-period are processed. Temperature changes are classified according to their magnitude and type in an attempt to capture the seasonal variability, trends and possible anomalies of SST in the Aegean region of Greece.

INTRODUCTION – RELATED WORK

In modern geospatial applications the aspect of time is becoming increasingly important. Invaluable information often resides in collections of images and maps portraying change over time. Towards this end, satellite imagery allows the mapping and geologic interpretation of Earth's surface (Chorowicz et al., 1989; Chorowicz et.al., 1992; Wan and Dozier, 1996). More specifically, current operational space-borne sensors in the thermal infra-red spectrum allow monitoring of the Earth's thermal field on a regular and frequent basis (Kilpatrick et al., 2001) over both land and sea surface. Several experimental observations indicate that thermal radiation is emitted from the ground prior to significant seismic events (Tronin, 1996; Cervone et al., 2004, Choudhury et al. 2006). Multi-temporal sea surface temperature (SST) imagery is used to identify and map the internal ocean dynamics such as sea water upwelling by other possible causes like convergence of sea currents and salinity-driven currents (Alexander et al., 1999). Nosov (1998) has shown a cold thermal SST anomaly related to underwater diastrophism (SST anomalies from underwater earthquakes). Additionally, data availability stimulated the analysis of a long time series of thermal images over Afar Depression (Ethiopia) (Miliaresis, 2009) by isolating the geothermal from both the seasonal and the earthquake-induced land surface temperature (LST) variability. The major hot spot evident in the area and the localized geothermal activity during the September 2005 seismic-volcanic crisis was successfully mapped. In another research effort, the terrain of Greece was segmented to regions on the basis of the multi-temporal MODIS LST data, with each region presenting a different thermal signature, expressing the biophysical suitability of spatial objects at moderate resolution scale (Miliaresis and Tsataris, 2009).

In this paper, a series of spatiotemporal (ST) filters are devised to convolve multi-temporal images in order to enhance the underlying temporal and spatial change information (Galic and Loncaric, 2001; Mennis et al., 2005). The spatial phenomena depicted in the images are continuous data types such as temperature, altitude, humidity, etc. termed as field data. Classic image convolution involves a series of filters-masks properly designed to selectively extract information taking into consideration the pixel grayscale intensity (Gonzalez and Woods, 2007). Our argument is that the crucial elements in multi-temporal imagery, are the ones describing change of the field data as they evolve through time. Interest primarily focuses on the retrieval of possible irregularities and the summarization of monitored change behaviors in various scales over space and time (Handcock and Csillag, 2004). Monthly averaged SST images are analyzed throughout a three year-period, in an attempt to expose possible patterns and hidden anomalies (Partsinevelos and Tryfona, 2006) in temperature fluctuations and assist decision making in environmental and urban planning at coastal regions.

MULTI-TEMPORAL IMAGE FILTERS

Motivation is drawn from spatial convolution of an image f(x, y) with a filter-mask w(s, t), designed to enhance or smooth selected frequencies across the image (equation 1).

$$g(x,y)=\sum_{s=-a}^{a}\sum_{t=-b}^{b}w(s,t)\,f(x+s,y+t) \quad , \quad a=(m-1)/2 \text{ and } b=(n-1)/2,\ \ m \times n\text{: odd numbers,} \qquad (1)$$

where g(x, y) is the resulting enhanced image, and m, n define the size of the filter w.

The transition from merely spatial to spatiotemporal (ST) filtering, incorporates long and short term temporal change of the field data upon ordered spatial areas. The spatiotemporal filter runs through a base image in a similar fashion as the spatial mask, but it additionally performs computations based on previous and succeeding temporal instances. In addition, the ST filter does not concentrate onto a single pixel where possible uncertainty and sensitivity resides due to the capturing process. Its ordered mode is defined by a group of pixels residing inside a defined parallelogram. In figure (1) the general shape of the described spatiotemporal filter is demonstrated.

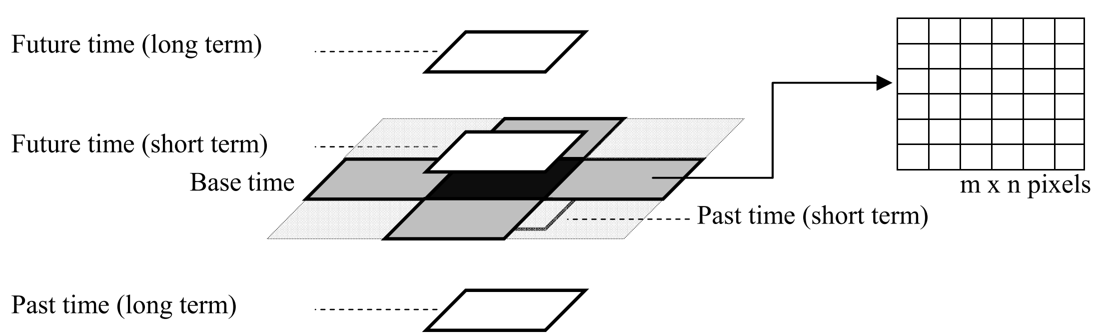


Figure 1. General shape of spatiotemporal filter, and indicative parallelogram pixel region.

By selecting appropriate weights, the spatial and temporal aspect may be differentiated in order to focus explicitly on each component. Weight variations include first and second derivative or polynomial based filters employed in both space and time. Beyond weights, other design variables include short term and long term temporal increments and spatial proximity specified by the neighboring space, which can include 4 or 8 connectivity regions (dark and light shaded regions shown in figure 1). In addition, selection of the ordered square spatial dimensions forces change estimation to become abstract and directional (North-South or East-West) and serve specific query applications. Design variables produce different change indices. Hence, short and/or long term change, smooth change, reversed or accumulated change is extracted, yielding patterns and possible anomalies.

Temporal Filters

In the temporal domain, in order to extract and enhance change, the weight of the central - base point is set to a positive value which equals to the sum of the past and future temporal weights of negative signs. Thus, rate of change is exaggerated as described by the second derivative met in Laplace spatial filters (Haralick and Shapiro, 1992). In figure (2a), the 3 x 3 matrix defines the spatial filter which for now remains empty apart from the middle point which is set to +4, contradicting the -1 weights in past-future and short-long term incidents. Larger middle weights and descending temporal weights inversely proportional to the distance from the present instance, generate higher sensitivity during change extraction (figure 2b). In order to differentiate between the raises and drops of data fluctuations, the sign of the resulted change is compared to the sign of the middle point's weight. Equal signs indicates an increase (hill) in the data depicted, while opposite signs suggests a local drop.

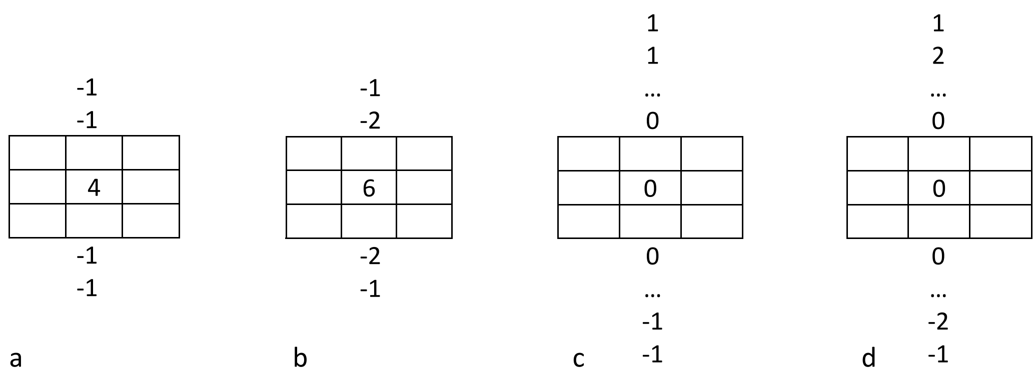


Figure 2. Weight variations of the temporal fraction for various ST filters.

Regular data change provides a smooth rate which may accumulate to considerable changes not captured by regular spatial filters. Attempting to describe the long term accumulated distant changes the weights of the filter are distributed as follows: the middle weight remains zero, while temporally distant neighbors in past and future times adopt symmetric weights yet of opposite signs, as shown in figures (2c, d). These filters resemble Sobel first derivative filters, yet they are dispersed far off the center according to the accumulation step.

Spatiotemporal Filters

In the spatiotemporal domain the above defined filters are combined with regular 2-dimensional spatial filters and are executed concurrently. The middle position weights compensate for both spatial and temporal weights. Laplace based ST filters indicate the rate of change and are shown in figure (3a). Sobel based filters are utilized to extract trends in basic orientations and are shown in figure (3b) where the short term of time is not considered.

	-1	
	-1	
0	-1	0
-1	8	-1
0	-1	0
	-1	
	-1	

a

	-2	
	0	
-1	-2	-1
0	0	0
1	2	1
	0	
	2	

b

	1	
	1	
-1	-2	-1
-2	12	-2
-1	-2	-1
	-1	
	-1	

c

0	0	-1
0	0	0
0	0	1
0	-1	0
0	0	0
0	1	0
-1	0	0
0	0	0
1	0	0

d

Figure 3. Weight variations of ST filters.

Based on the generic filters described, more complex weight distributions may be selected in order to establish a change classification. One should be cautious in the filter application since change may be depicted in the next image instance than the one processed just like the spatial translation of the lines extracted from an image (Gonzalez and Woods, 2007). E.g., the filter shown if figure (2a) for a drop in data value, gives a positive to negative transition, while an instantaneous increase of the value gives a negative - positive - negative transition. A complex filter which resembles Laplace in space and Sobel in time is shown in figure (3c). Temporal direction examination is plausible under a three dimensional cube filter, where the weights in the direction of interest are set to 0, while the neighbor weights are opposite as shown in figure (3d).

Area Clustering

Apart from ordered regions the base unit for filtering may become a user-defined area of interest or automatically clustered region. Nevertheless, for the user defined region selection, the process does not run throughout the image, but concentrates to the specified spatial dimensions and weighted proximity regions as shown in figure (4). Moreover, K-Means cluster analysis divides the imagery into K exclusive clusters (Mather, 2005). A cluster example for a region of Greece is presented in figure (4 right). The ST filters are applied accordingly but spatial neighborhoods are defined as zones in accordance with image morphologic dilation. This approach is not further examined in the current paper.

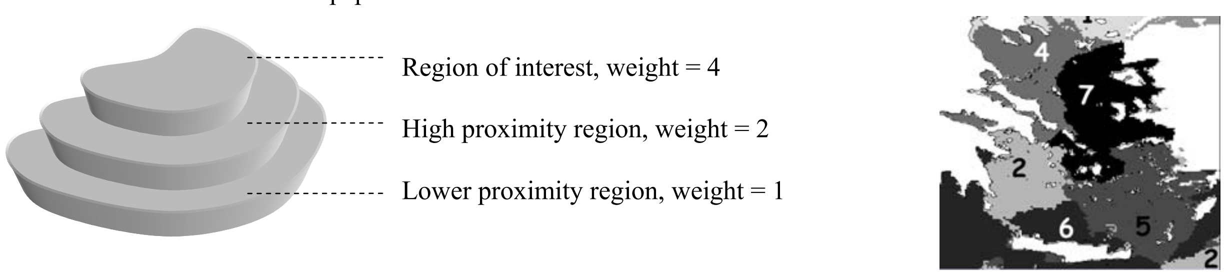


Figure 4. User defined cluster for ST filtering and automated clustering.

OVERALL REPRESENTATIVE CHANGE SIGNATURE

Through the ST filtering, each image from the multi-temporal dataset results in a spatially condensed change image relative to the parallelogram cluster selection. The resulting image is further thresholded in order to communicate only the "significant" (based on the application) portion of change. The series of these new multi-change images collapse to a 3-dimensional cloud of points classified in magnitude or type and form the "change space". Subsequently, the change space is further examined to capture and convey the summarized behavior of the entire dataset. Thus, a second objective rises: the construction of representative trend structures capable of visually conveying change information (Tominski et al., 2005; Aigner et al., 2007). In order to generate these trend structures we utilize the self-organizing map (SOM) network. This type of artificial neural network is characterized by unsupervised and competitive learning often used as a method for information abstraction (Kohonen, 2001; Partsinevelos et al., 2005). Its unsupervised character is established through the automation of the procedure without any a priori human interaction on the input dataset. Generally, a set of connected multi-dimensional nodes forming a polyline attempts to geometrically best map a multi-dimensional input space. In our case, the input space consists of the change points over the pre-specified thresholds associated to the filters used. The outcome of this analysis serves two purposes. First, a concise and inclusive representation of the input space is performed for visualization purposes. Second, it facilitates examination of possible associations between different datasets.

Throughout the presented processes abstraction is evident in various design elements. First, in the spatial level connectivity neighbors are correlated providing a neighbor based rather than a pixel based approach. Second, rectangle areas are the base elements of filtering which again depict region based processing. In the same fashion, temporal regions are considered while time is not perceived as instantaneous but more like spanning from past to future in short or long term varying temporal blocks. The whole process blends spatial and temporal change under the same descriptive signature and actually models a multi-temporal dataset into a 3-dimensional polyline.

CASE STUDY – EXPERIMENTATION

In order to demonstrate the applicability of the described ST filtering we utilize datasets from Terra and Aqua satellites which provide the great advantage of the MODerate-resolution Imaging Spectroradiometer (MODIS) imagery, available on day and night basis (Wan et al., 2004; Miliaresis, 2009). Towards this end, monthly day and night averaged SST images are analyzed throughout a three year-period, in an attempt to capture the seasonal variability of SST in the region of Greece. A sample of the imagery is shown in figure (5). Short term temporal increment adheres to monthly variance while long term temporal increment refers to annual variance. This type of annual comparison for each month partially compensates for annual periodicity.

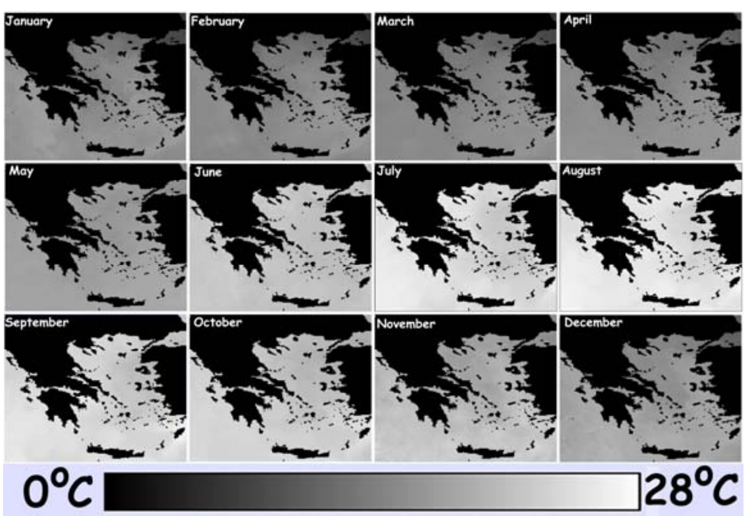
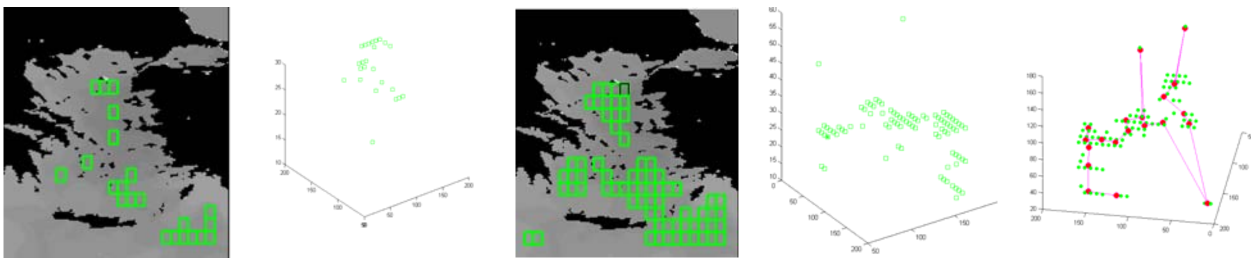


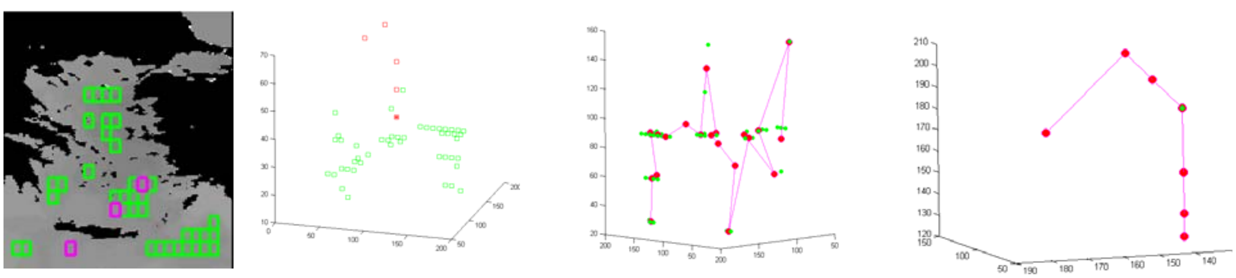
Figure 5. Sample of multi-temporal MODIS imagery.

In the implemented algorithm, the user may provide the filter weights, the temporal short and long term distances, the size of the parallelogram and the types of change in accordance to the filter type. The performance of the ST filter shown in figure (3a) upon the dataset of figure (5) is graphically evident in figures (6a, b) in 2-d and 3-d forms. In figures (6c, d) a more sensitive change filter including larger weights is used, resulting in additional change occurrences. Figure (6e) depicts the SOM representative signature. In figure (7a) the ST filtering resulted in two change types, and the SOM algorithm yielded two signatures (figures 7a, b). In figure (8a) the temporal filter of the figure (2c) depicts accumulated changes. Finally, figures (8b, c) show trends of various change types and magnitudes depicted through different colors and symbols.



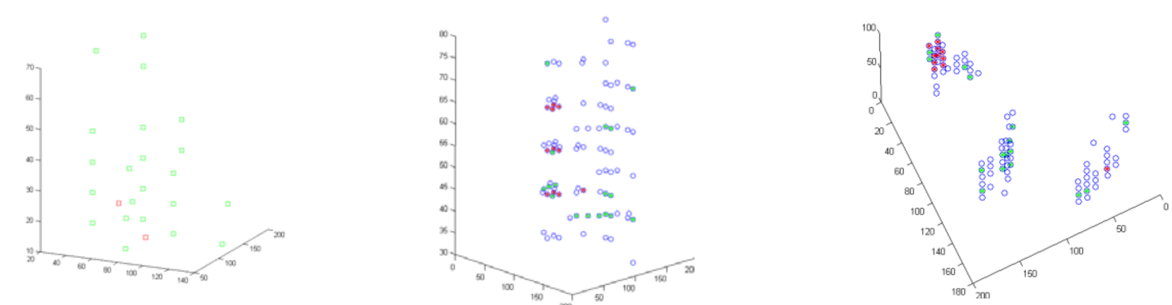
a. b. c. d. e.

Figure 6. a) ST filtering in 2-d, b) resulting point cloud in 3-d, c) ST filtering of larger weights, d) resulting point cloud in 3-d, and e) SOM signature.



a. b. c. d.

Figure 7. a) ST filtering with two change types, b) resulting 3-d point cloud, c and d) SOM signatures for the two change types.



a b c

Figure 8. a) Accumulative change extraction, b and c) ST filtering showing varying change types and magnitudes.

CONCLUSIONS AND FUTURE DIRECTIONS

In this work we provided an introduction for a series of novel spatiotemporal filters which selectively and under temporal and spatial scaling enhance data analysis of multi-temporal imagery. These filters are statistical in nature since they are applied on regions rather than pixels in order to provide more generalized and error free results. Change is classified according to the design of the ST filters in orders of magnitude, direction, and type. Finally, a SOM network visually summarized the ST filtering outcome to provide representative trend signatures. Thorough specification and experimentation could lead these classic resembling filters to become a common ground for a first step quick processing of multi-temporal field data.

Some considerations need to be addressed for a more comprehensive approach. First, regularity of change should be configured through statistics of the imagery in order to formulate the thresholds which represent important change. A multi-variant adaptive filter could be devised which would change its size according to the data variation included in each rectangle region. Moreover, the resulted spatiotemporal change space should be formulated directly from the filter application allowing different values in every pixel instead of the near-binary thresholded mode described in this paper. These values should indicate relative change weights upon which the SOM algorithm should be performed. In addition, various clustering and network based algorithms should be utilized to provide representative networks of change instead of a single ambiguous SOM signature. Finally, changes in the region considered should be evaluated and justified as of their cause but these issues should be addressed from experts in relative disciplines.

REFERENCES

Aigner, W., Miksch, S., Müller, W., Schumann, H. and Tominski, C., 2007. Visualizing time-oriented data-A systematic view. *Computers and Graphics*, 31(3):401-409.

Alexander, M. A., Deser, C. and Timlin, M. S., 1999. The reemergence of SST anomalies in the North Pacific Ocean. *J. Climate*, 12:2419–2431.

Cervone, G., Kafatos, M., Napoletani, D. and Singh, R., 2004. Wavelet maxima curves of surface latent heat flux associated with two recent Greek earthquakes. *Natural Hazards and Earth System Sciences*, 4:359–374.

Chorowicz, J., Kim, J., Manoussis, S., Rudant, J.P, Foin, F. and Veillet, I., 1989, A new technique for recognition of geological and geomorphological patterns in digital terrain models. *Remote Sensing of Environment*, 29:229-239.

Chorowicz J., Deffontaines, B., Huaman-Rodrigo, D., Guillande, R., Leguern, F. and Thouret, J.C., 1992. SPOT satellite monitoring of the eruption of Nevado Sabancaya volcano (Southern Peru). *Remote Sensing of Environment* 42:43-49.

Choudhury, S., Dasgupta, S., Saraf, A. K. and Panda, S.K., 2006. Remote sensing observations of pre-earthquake thermal anomalies in Iran. *International Journal of Remote Sensing*, 27:4381-4396.

Galic, S. and Loncaric, S., 2001. Cardiac image segmentation using spatio-temporal clustering. In: *Proceedings of SPIE Medical Imaging*. San Diego, USA, pp. 1199-1206.

Gonzalez, R. C. and Woods, R. E., 2007. *Digital Image Processing*. Prentice Hall, Upper Saddle River, NJ.

Handcock, R. N. and Csillag, F., 2004. Spatio-temporal analysis using a multiscale hierarchical ecoregionalization. *Photogrammetric Engineering and Remote Sensing*, 70:101–110.

Haralick, R. and Shapiro L., 1992. *Computer and Robot Vision*. Addison-Wesley Publishing Company, vol 1.

Kilpatrick, K.A., Podesta, G.P. and Evans, R., 2001. Overview of the NOAA/NASA Advanced Very High Resolution Radiometer Pathfinder algorithm for sea surface temperature and associated matchup database. *Journal of Geophysical Research*, 106(C5):9179-9197.

Kohonen, T., 2001. *Self-Organizing Maps*. Springer, Berlin.

Mather, P.M., 2005. *Computer processing of remotely-sensed images*. John Wiley and Sons, England.

Mennis, J., Viger, R. and Tomlin, C.D., 2005. Cubic map algebra functions for spatio-temporal analysis. *Cartography and Geographic Information Science*, 32(1):17-32.

Miliaresis, G., 2009. Regional thermal and terrain modeling of the Afar Depression from multi-temporal night LST data. *International Journal of Remote Sensing*, 30, 18 pages, doi:10.1080/01431160802562271 [in press].

Miliaresis, G. and Tsatsaris A., 2009. Thermal terrain modeling of spatial objects, a tool for environmental and climatic change assessment. *Environmental Monitoring & Assessment*, 151, 12 pages, doi:10.1007/s10661-009-0913-x, [in press].

Nosov, M.A., 1998. Ocean surface temperature anomalies from underwater earthquakes. *Volcanology and Seismology*, 19:371-376.

Partsinevelos, P., Agouris, P. and Stefanidis, A., 2005. Reconstructing spatiotemporal trajectories from sparse data, *Journal of Photogrammetry and Remote Sensing*, Elsevier Science, 60: 3-16.

Partsinevelos, P. and Tryfona N., 2006. Handling high-level queries in location-based services for user groups, *Geoinformatica*, 10(2):213-234.

Tominski, C., Schulze-Wollgast, P. and Schumann, H., 2005. 3D information visualization for time dependent data on maps. In: *9th International Conference on Information Visualisation*, London, UK, pp.175-181.

Tronin, A., 1996, Satellite thermal survey- a new tool fot the study of seismoactive regions. *International Journal of Remote Sensing*, 17:1439-1455.

Wan, Z. and Dozier, J., 1996, A generalized split-window algorithm for retrieving land surface temperature from space. *IEEE Trans. Geosciences and Remote Sensing*, 34:892-905.

Wan, Z., Zhang, Y., Zhang, Q. and Li, Z.-L., 2004. Quality assessment and validation of the MODIS land surface temperature. *International Journal Remote Sensing*, 25:261-274.

SPATIOTEMPORAL FILTERING OF MULTI-TEMPORAL IMAGES: APPLICATION ON MODIS SEA SURFACE TEMPERATURE (SST) IMAGERY

MultiTemp 2009 – 5th International Workshop on the Analysis of Multi-temporal Remote Sensing Images July 28-30, 2009, Connecticut

Panagiotis Partsinevelos
Technical University of Crete
Department of Mineral Resources Engineering
email: ppartsi@mred.tuc.gr

George Miliaresis
University of Patras
Geology Department
email: gmiliar@upatras.gr

ABSTRACT

A series of **spatiotemporal (ST) filters** are devised in order to retrieve change information **from multi-temporal imagery** depicting continuous-field data. Based on common spatial filters, derivative and new complex filters are designed to assist information retrieval under various application perspectives, including **merely temporal, abrupt, gradual, directional and user defined spatiotemporal change**. ST filtering of multi-temporal imagery results in a **new multi-change dataset** depicted as a 3-dimensional cloud of points classified in magnitude and/or type. This dataset is further examined to capture and visually convey **an overall summarized change behavior**. Thus, a **self organizing map algorithm** is utilized, spreading along the change space and forming a 3-dimensional representative -signature polyline.

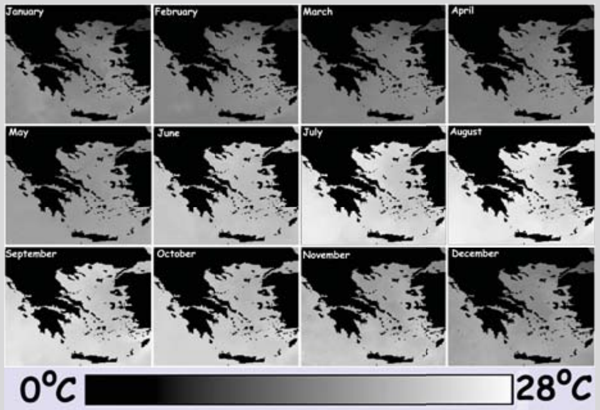


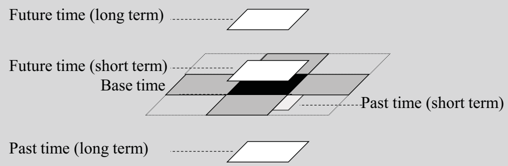
Figure: To demonstrate the applicability of the proposed ST filters, monthly averaged sea surface temperature (SST) Modis images throughout a three year-period are processed. Temperature changes are classified according to their magnitude and type in an attempt to capture the seasonal variability, trends and possible anomalies of SST in the Aegean region of Greece.

OUTLINE

- Spatiotemporal (ST) filter implementation,
- 3D change space formation through ST filtering of multi-temporal imagery classified in magnitude and/or type,
- Overall summarized change signature extraction through a self organizing map.

A. FILTER CONSTRUCTION

- Transition from merely spatial to spatiotemporal (ST) filtering
- Incorporation of long and short term temporal change
- ST filtering in a pixel group defined from a parallelogram (not a single pixel process where uncertainty resides)

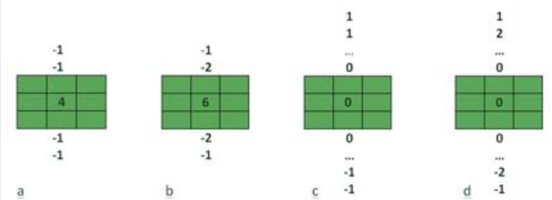


Figure, general shape of the spatiotemporal filter.

Design properties:

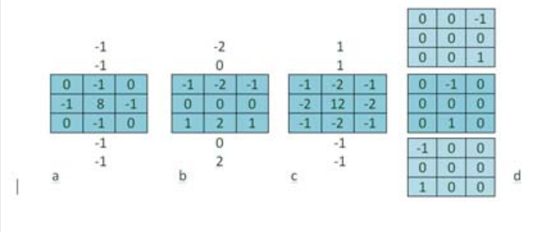
- **Appropriate weights**, (spatial and temporal aspect may be differentiated in order to focus explicitly on each component),
- **Short term and long term temporal increments,**
- **Spatial proximity** specified by the neighboring space, which can include 4 or 8 connectivity regions,
- **Parallelogram dimensions** forces change estimation to become abstract and directional,

Hence, short and/or long term change, smooth change, reversed or accumulated change is extracted, yielding patterns and possible anomalies.



Temporal Filters

In order to differentiate between raises and drops of data fluctuations, the sign of the resulted change is compared to the sign of the middle point's weight.



Spatiotemporal Filters

In the spatiotemporal domain, temporal filters are combined with regular 2-dimensional spatial filters (Laplace, Sobel, etc) and are executed concurrently.

B. CHANGE SPACE FORMATION

Through ST filtering, each image from the multi-temporal dataset results in a spatially condensed change image relative to the parallelogram cluster selection. The resulting image is further thresholded in order to communicate only the "significant" (based on the application) portion of change. The series of these new multi-change images collapse to a 3-dimensional cloud of points classified in magnitude or type and form the "change space".

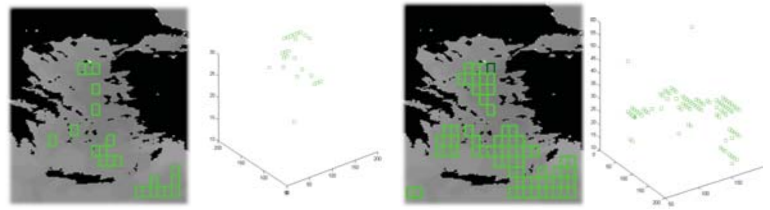


Figure: Change parallelograms upon the base imagery and corresponding change space point set.

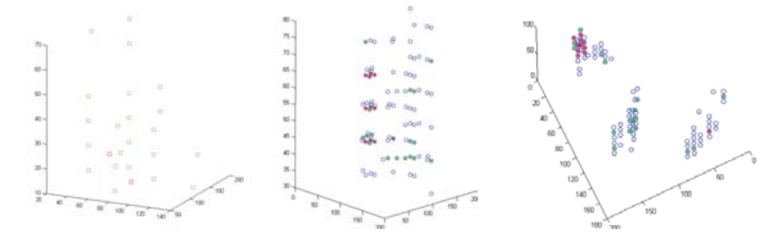


Figure: Accumulative change extraction, and ST filtering showing varying change types and magnitudes.

C. 3D CHANGE SIGNATURE

Construction of representative trend structures capable of visually conveying change information upon the change space. In order to generate these trend structures we utilize the self-organizing map (SOM) network.

The outcome of this analysis serves two purposes. First, a concise and inclusive representation of the input space is performed for visualization purposes. Second, it facilitates examination of possible associations between different datasets.

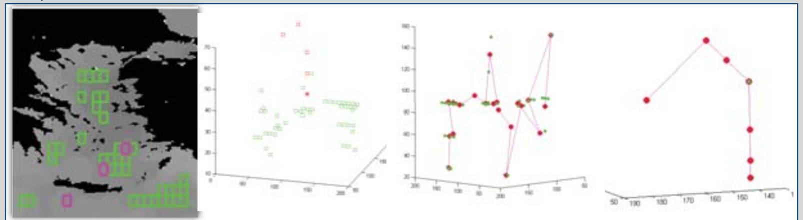


Figure: a) ST filtering with two change types, b) resulting 3-d point cloud, c and d) SOM signatures for the two change types.

CONCLUSIONS

We introduce a series of novel spatiotemporal filters which selectively and under temporal and spatial scaling enhance data analysis of multi-temporal imagery. Change is classified according to the design of the ST filters in orders of magnitude, direction, and type. A SOM network visually summarizes the ST filtering outcome to provide representative trend signatures. Thorough specification and experimentation could lead these classic resembling filters to become a common ground for a first step quick processing of multi-temporal field data.

The whole process blends spatial and temporal change under the same descriptive signature and actually models a multi-temporal dataset into a 3-dimensional polyline.

In each application and attribute data considered, change and its interpretation should be evaluated from experts in relative disciplines.