A TIME-SERIES SEMANTIC-COMPUTING METHOD FOR 5D WORLD MAP SYSTEM

YASUSHI KIYOKI,[1, 2, 3] ASAKO URAKI,[1, 2] SHIORI SASAKI,[1, 2, 3]
YUKIO CHEN[4]

[1] Keio University, Graduate School of Media and Governance, Kanagawa, Japan
kiyoki@sfc.keio.ac.jp, aco@sfc.keio.ac.jp, ssasaki@musashino-u.ac.jp
[2] Keio University, SFC Research Institute, Kanagawa, Japan
kiyoki@sfc.keio.ac.jp, aco@sfc.keio.ac.jp, ssasaki@musashino-u.ac.jp
[3] Musashino University, Graduate School of Data Science, Tokyo, Japan
kiyoki@sfc.keio.ac.jp, ssasaki@musashino-u.ac.jp
[4] Kanagawa Institute of Technology, Department of Information & Computer Sciences, Kanagawa, Japan
chen@ic.kanagawa-it.ac.jp

"Semantic space creation" and "distance-computing" are basic functions to realize semantic computing for environmental phenomena memorization, retrieval, analysis, integration and visualization. We have introduced "SPA-based (Sensing, Processing and Actuation) Multi-dimensional Semantic Computing Method" for realizing a global environmental system, "5-Dimensional World Map System". This method is important to design new environmental systems with Cyber-Physical Space-integration to detect environmental phenomena occurring in a physical-space (real space). This method maps those phenomena to a multi-dimensional semantic-space, performs semantic computing, and actuates the semantic-computing results to the physical space with visualizations for expressing environmental phenomena, causalities and influences. As an actual system of this method, currently, the 5D World Map System is globally utilized as a Global Environmental Semantic Computing System, in SDG14, United-Nations-ESCAP: (https://sdghelpdesk.unescap.org/toolboxes). It is significant to memorize those situations and compute environmental change in various aspects and contexts, in order to discover actual phenomena occurring in the nature of our planet.

Keywords:
cyber & physical space integration, SPA-function, spatio-temporal computing, semantic computing, world map-based visualization, warning message propagation

University of Maribor Press

DOI https://doi.org/10.18690/um.feri.5.2023.3
ISBN 978-961-286-745-4

1 Introduction

We have introduced the architecture of a global environmental system, "5-Dimensional World Map System" [3,4,6,10], to realize environmental knowledge memorization, sharing, retrieval, integration and visualization with semantic computing. The basic space of this system consists of a temporal (1st dimension), spatial (2nd, 3rd and 4th dimensions) and semantic dimensions (5th dimensions), representing a large-scale and multiple-dimensional semantic space. This space memorizes and recalls various environmental knowledge expressed in multimedia information resources with temporal, spatial and semantic correlation computing functions, and realizes a 5D World Map for dynamically creating temporal-spatial and semantic multiple views.

We also introduce the concept of "SPA (Sensing, Processing and Analytical Actuation Functions)" for realizing an global environmental system, to apply it to our 5-Dimensional World Map System. This concept is effective and advantageous to design environmental systems with Cyber-Physical integration to detect environmental phenomena as real data resources in a physical-space (real space), map them to cyber-space to make analytical and semantic computing, and actuate the analytically computed results to the real space with visualization for expressing environmental phenomena, causalities and influences.

Semantic computing [1,2,5] is an important and promising approach to semantic analysis for various environmental phenomena and changes in a real world. This paper presents a new concept of *"Time-series-Analytical Semantic-Space and Computing for environmental phenomena*" for realizing global environmental analysis [8,9,10,11,13,14]. This space and computing method are based on semantic space creation with time-analysis for analyzing and interpreting environmental phenomena and changes occurring in the world. We focuse on semantic interpretations of time-series data, as an experimental study for creating *"Time-Series Analysis Semantic-Space for environment.*"

2 Global Environmental Analysis with Semantic Computing

We have introduced "5D World Map System" with Spatio-Temporal and Semantic Computing in SPA, as the architecture of a multi-visualized and dynamic knowledge representation system [3,4,6,10]" applied to environmental analysis and semantic computing. The basic space of this system consists of a temporal (1st dimension), spatial (2nd, 3rd and 4th dimensions) and semantic dimensions (5th dimension, representing a large-scale and multiple-dimensional semantic space). This space memorizes and recalls various multimedia information resources with temporal, spatial and semantic correlation computing functions, and realizes a 5D World Map for dynamically creating temporal-spatial and semantic multiple views applied for various "environmental multimedia information resources."

2.1 Semantic Computing in 5D World Map System

We have presented the dynamic evaluation and mapping functions for multiple views of temporal-spatial metrics and integrate the results of semantic evaluation to analyze environmental multimedia information resources[3,4,6,10]. Our semantic computing system realizes the interpretations on "semantics" and "impressions" of environmental phenomena with multimedia information resources, according to "contexts"[1,2,5]. The main feature of this system is to create world-wide global maps and views of environmental situations expressed in multimedia information resources (image, sound, text and video) dynamically, according to user's viewpoints. Spatially, temporally, semantically and impressionably evaluated and analyzed environmental multimedia information resources are mapped onto a 5D time-series multi-geographical space. The basic concept of the 5D World Map System is shown in Figures 1 and 2. The 5D World Map system applied to environmental multimedia computing visualizes world-wide and global relations among different areas and times in environmental aspects, by using dynamic mapping functions with temporal, spatial, semantic and impression-based computations [3,4,6,10,11,13].

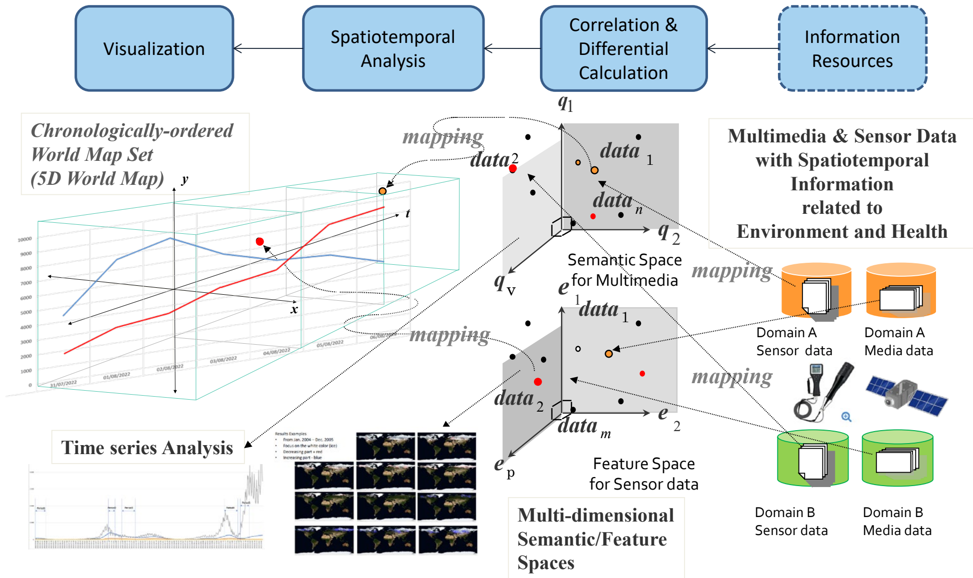


Figure 1: 5D World Map System for world-wide semantic computing for Global Environmental Analysis

Source: own.

2.2 SPA: Sensing, Processing and Analytical Actuation Functions in 5D World Map

"SPA" is a fundamental concept for realizing environmental systems with three basic functions of "Sensing, Processing and Analytical Actuation" for Physical-Cyber integration. "SPA" is effective and advantageous to detect environmental phenomena as real data resources in a physical-space (real space), map them to the cyber-space to make analytical and semantic computing, and actuate the analytically computed results to the real space by visualization for expressing environmental phenomena with causalities and influence. This concept is applied to our semantic computing in 5D World Map System, as shown in **Figure 1, Figure 2** and **Figure 3**.

The important application of the semantic computing system are "Global Environment-Analysis" for making appropriate and urgent solutions to global environment changes in terms of short and long-term changes. The "six functional-pillars" are essentially important with "environmental knowledge-base creation" for sharing, analyzing and visualizing various environmental phenomena and changes in a real world.

The 5D World Map System realizes Cyber-Physical Space-integration, as shown in **Figure 1**, to detect environmental phenomena with real data resources in a physical-space (real space), map them to the cyber-space to make knowledge bases and analytical computing, and actuate the computed results to the real space with visualization for expressing environmental phenomena, causalities and influences. The 5D World Map System and its applications create new analytical circumstance with the SPA concept (Sensing, Processing and Analytical Actuation) for sharing, analyzing and visualizing natural and social environmental aspects. This system realizes "environmental analysis and situation-recognition" which will be essential for finding out solutions for global environmental issues. The 5D World Map System collects and facilitates a lot of environmental information resources, which are characteristics of ocean species, disasters, water-quality and deforestation.

3 A Time-series Semantic Computing Method for Global Environmental Analysis

We introduce a concept of "time-series-context", as a context on time-series in semantic computing on a multi-dimensional space. The "time-series-context" is a data structure to specify dimensional projection(dimensional selection), that is, the projection (selection of dimensions) to be applied in "time-series semantic computing."

- One of the most important processes of multi-dimensional & time-series semantic computing is to define semantic "time-series-context".
- It is essential to compare between two different time-series on semantic features, expressing a time-series-context, for realizing semantic interpretations and predictions on natural environmental phenomena.

We define a multi-dimensional & time-series semantic computing method for time-series data in a time axis with the definition of time-series context.

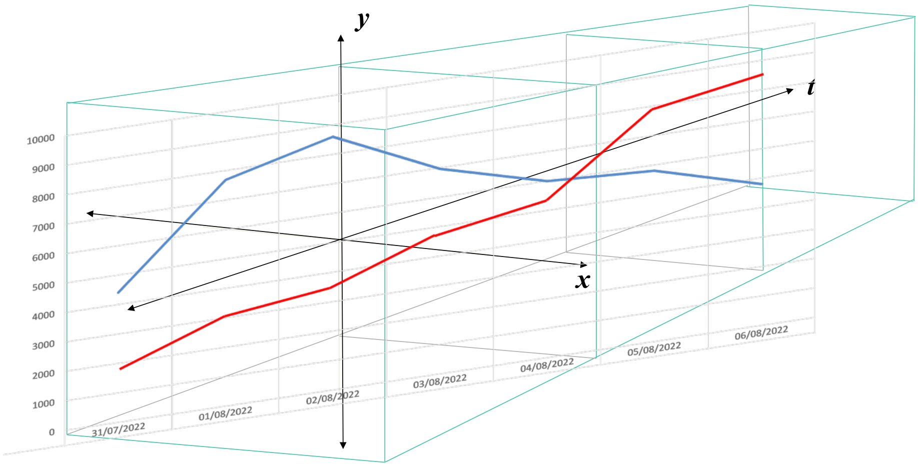


Figure 2: A Time-series Semantic-Computing Space for 5D World Map System

Source: own.

3.1 Basic data structures and operations

The basic data structures for time-series semantic computing are defined as follows:

- Space: Multi-Dimensional semantic space with time-axis
- Basic elements: point-series --> time-series (point-series along a time-series for expressing a phenomenon)
- Time-series-context: "time-series grain" & "time-interval"

3.2 Semantic computing process

To define a time-series-context, we express semantic meaning of temporal difference and its interpretations according to the time-series-context.

- If switching the N time-series-contexts for same data, we can obtain N different semantic meanings of temporal difference in each context.
- The definition of the time-series-context by the 3 steps is corresponding to set the closed world on time axis.

Step 1: Define semantic viewpoint to fix target axes, that are corresponding to multiple parameters as the semantic feature combination, reflecting expert-knowledge and viewpoint.

Step 2: Define semantic viewpoint to fix target time-series data to calculate semantic distances,

3.3 Semantic computing functions

In this section, we express the data structures and functions for "time-series stream-creation". The following 6 basic functions are defined to express the query-time-series, that creates time-series query expression as a new time-series stream:

(1) Time-series data structures

To realize "time-series stream-creation" (creating time-series stream), the following basic settings on time-series data structures are defined:

(1-1) "time-granularity (granularity in time)" setting,
(1-2) "time-interval" setting,
(1-3) "time-grains-combination" setting,
(1-4) "time-series-context" setting.

(2) Time-series stream

A time-series stream is defined with a basic-atomic-time-element, that is expressed:

(2-1) basic-atomic-time-element form: (time-i, (value-i-1, value-i-2, ---, value-i-m)).

(2-2) Time-series stream expression:

By combining basic-atomic-time-elements, any time-series stream is expressed and created. (time-grain setting, time-interval setting, time-grains-combination)

Time-series stream expressions:

Time-series-semantic-integration-method:
Temporal-Atomic-element:(time-series), as the time-grain setting:
((time-1, (value-1-1, value-1-2, ---, value1-m)) ,
(time-2, (value-2-1, value-2-2, ---, value-2-m)), ---,
(time-n, (value-n-1, value-n-2, ---, value-n-m))):

Atom-1:
((t-1,t-2,t-3)(v-1-i,v-2-i,v-3-i)) (The "i" is fixed with a "time-series context".)
Atom-2:
((t-1,t-2,t-3)(v-1-j,v-2-j,v-3-j))
Atom-3:
((t-1,t-2,t-3)(v-1-k,v-2-k,v-3-k))

(2-3) Time-series-semantic-integration (Time-series stream is expressed and created in the following basic structures): (time-grains-combination for time-interval setting,)

(2-3-1) Vertical integration for time-series stream:
(((t-1,t-2,t-3)(v-1-i,v-2-i,v-3-i)), ((t-1,t-2,t-3)(v-1-j,v-2-j,v-3-j)),
((t-1,t-2,t-3)(v-1-k,v-2-k,v-3-k))) - - -

(2-3-2) Horizontal integration for time-series stream:
((t-1,t-2,t-3) ((v-1-i,v-1-j,v-1-k), (v-2-i,v-2-j,v-2-k), (v-3-i,v-3-j,v-3-k)))

(2-3-3) Time-series stream integration:

(((t-1,t-2,t-3), ((t-4,t-5,t-6)) (((v-1-i,v-1-j,v-1-k), (v-2-i,v-2-j,v-2-k),
(v-3-i,v-3-j,v-3-k))), ((v-4-i,v-4-j,v-4-k), (v-5-i,v-5-j,v-5-k),
(v-6-i,v-6-j,v-6-k)))

(3) Geographical-time-series form:

Geographical time-series stream, as a time-series stream, is defined with a basic-geo-atomic-time-element, that is expressed:

(3-1) basic-geo-atomic-time-element form:

S1(place1) (time-1, (value-1-1, value-1-2, ---, value-1-m))
(time-2, (value-2-1, value-2-2, ---, value-2-m))
(time-3, (value-3-1, value-3-2, ---, value-3-m))

S2(place2) (time-4, (value-4-1, value-4-2, ---, value-4-m))
(time-5, (value-5-1, value-5-2, ---, value-5-m))
(time-6, (value-6-1, value-6-2, ---, value-6-m))

S3(place3) (time-7, (value-7-1, value-7-2, ---, value-7-m))
(time-8, (value-8-1, value-8-2, ---, value-8-m))
(time-9, (value-9-1, value-9-2, ---, value-9-m))

(4) Time-series-stream-comparison (semantic-distance computing between two time-series streams)

(4-a) distance of features (time-series-context features) between different timings in same time-series

(4-b) distance of features (time-series-context features) between different phenomena in different time-series

(4-c) distance of features (time-series-context features) between different places (geographical places) in the same phenomena in different time-series

The basic distance function between two time-series streams is defined in the following form:

Timeseries-streams-distance((t1, t2, ---, tn) (y1, y2, ---, yn) , (t1', t2', ---, tn') (y1', y2' ---, yn')).

(4-1) Timeseries-streams-distance as the sum of each parameters' distances:

Timeseries-streams-distance-1((t1, t2, ---, tn) (y1, y2, ---, yn) , (t1', t2', ---, tn') (y1', y2' ---, yn')) => $\Sigma(i=0, n)\ |yi - yi'|$

(4-2) Timeseries-streams-distance as distance-in-time-interval-normalization:

Timeseries-streams-distance-2((t1, t2, ---, tn) (y1, y2, ---, yn) , (t1', t2', ---, tn') (y1', y2' ---, yn')) =>
distance-in-time-interval-normalization ((t1, t2, ---, tn) (y1, y2, ---, yn) ,
(t1', t2', ---, tn') (y1', y2' ---, yn'))

(4-3)Timeseries-streams-distance as distance-in-start-time-normalization

Timeseries-streams-distance-3((t1, t2, ---, tn) (y1, y2, ---, yn) , (t1', t2', ---, tn') (y1', y2' ---, yn')) =>
distance-in-start-time-normalization ((t1, t2, ---, tn) (y1, y2, ---, yn) ,
(t1', t2', ---, tn') (y1', y2' ---, yn'))

(5) Geographical phenomenon-distance function form is defined for time-series comparison between different places.

Geographical-timeseries-streams-distance((S1(place1),((time-1, (value-1-1, value-1-2, ---, value-1-m)), (time-2, (value-2-1, value-2-2, ---, value-2-m)), (time-3, (value-3-1, value-3-2, ---, value-3-m))), (S2(place2),(time-4, (value-4-1, value-4-2, ---, value-4-m)), (time-5, (value-5-1, value-5-2, ---, value-5-m)), (time-6, (value-6-1, value-6-2, ---, value-6-m))))

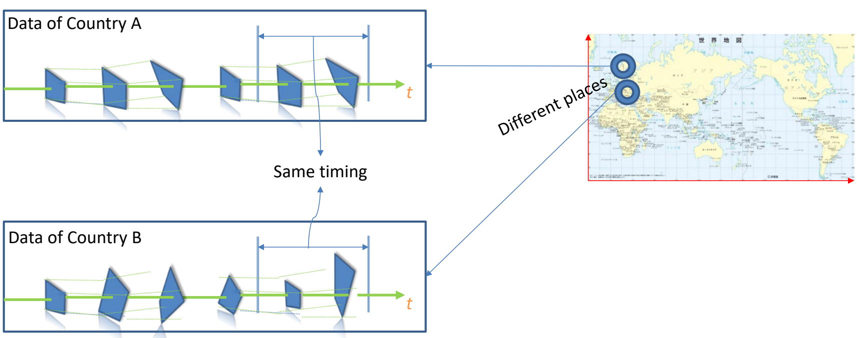


Figure 3: The Concept of a difference comparison with Time-series Semantic-Computing with 5D World Map System

Source: own.

3.4 Time-series semantic computing for phenomenon-prediction with time-interval ratio

We present a ratio computing method for phenomenon-prediction with time-interval ratio between peak values. This method predicts the timing of future peak with differential computing, according to "time-series-context".

The basic data structure of "time-series context" is defined in 6 Key elements:

- Original time-granularity (granularity in time) (OG)
- Target timing-granularity (TG)
- Feature extraction method (FEM)
- Focusing time-interval (FW) (time-interval)
- Differential computing method (DCM)
- Pivot extraction method on ITD (PEM)

Two time-series data (IRD, ITD) consists of time and its corresponding values expressed in target granularity in two different places, F and J. The ratio computing method is applied to three peaks of the corresponding values existing in IRD(FT1, FT2, FT3) in timing in the place F, and three peaks in ITD(JT1, JT2, "JT3(target for estimation)")) in the place J. Then, JT3 is computed as an estimated timing in the following process, as the timing when the situation corresponding to the third peak will occur in the future in the place J.

The important feature of this method is to define differential computing function as ratio computing between the timing of the peaks in time-series data to estimate the future peak.

Input data for analysis (IRD) = Time-series sequence of (parameter-value, time-point) for expressing the situation with the selected parameter in the place F:

- The number of confirmed-values in the place F.

Input data for prediction (ITD) = Time-series sequence of (parameter-value, time-point) for expressing the situation with the selected parameter in the place J:

– The number of confirmed-values in the place J.

As for the 6 key elements to express time-series-context, we applied the followings. Meaning of the 6 key elements settings is to determine the common situation in two different time-series, as "time-series-context".

The 6 Key elements are expressed as a "time-series-context" for phenomenon-prediction with time-interval ratio between peak values:

The "time-series-context" definition is set in the following:

– Original time-granularity (granularity in time) = daily
– Target timing-granularity (TG) = peaks
– Feature extraction method (FEM) = time point of peaks
– Focusing time-interval (FW) = from first peak to the last peak 3 or more peaks that matched condition(condition ：)
– Differential computing method (DCM) = ratio computing function for the number of days between the selected adjacent peaks, by applying average, difference, and other functions
– Pivot extraction method on ITD (PEM) = most recent 2 or more peaks that matched condition(condition ：)

The prediction process with the differential computing method (DCM) is defined as the ratio computing function for computing the number of days between the selected adjacent peaks, by applying average, difference, and other operations.

The basic data structure for the prediction with the differential computing method is expressed:

FT1-3: time points at 3 peaks (FT1, FT2, FT3) timings, corresponding to top-three maximum parameter-values in the time-series sequence in the place F.

JT1-3: time points at 3 peaks (JT1, JT2, "JT3 (target for estimation)") timings, corresponding to top-three maximum parameter-values in the time-series sequence in the place J.

The process for the prediction with the differential computing method is expressed:

(Step-1) 3 peaks selection (FT1, FT2, FT3) in time series in IRD,
(Step-2-1) ratio computing in time-interval: (FT3-FT2)/(FT2-FT1),
(Step-2-2) average computing in time-interval: average((FT3-FT2), (FT2-FT1)),
(Step-2-3) differential computing in time interval: (FT3-FT2) => JT3-JT2 = (FT3-FT2)
(Step-3) (JT3-JT2)/(JT2-JT1) = (FT3-FT2)/(FT2-FT1) => JT3 is computed as an estimated time of peak-3 in this ratio computing if (2-1) is applied.

Then, JT3 is obtained as the prediction result of a next peak timing, occurring in the future.

4 Time-series semantic computing in 5D World Map System

We have integrated the time-series semantic computing method into the 5D World Map System. The following cases are example targets of semantic computing in 5D World Map System with geographical time-series stream defined with a basic-geo-atomic-time-element in Section 3: Time-series semantic computing for Global Environmental Analysis.

4.1 Case I: Earthquake analysis with time-series semantic computing on 5D World Map System

This case shows the analysis of the depth of earthquakes, which occurred around the world during the period from Aug. 23rd to Aug. 28th, 2014, and Jan 7th to Jan. 13th, 2023. The target data is acquired from USGS Earthquake Feeds.

Figure 4 shows the visualization results of the time-series change of geographical distribution of the depth values of significant earthquakes with over 2.5 magnitude values in one week of August 2014. From the results, we can observe intuitively that there is a point where deep earthquakes had happened through the whole period (eg.

Alaska), and there is an emergent timing that deep earthquakes happened in Fiji (2014/08/25) and consequently in Japan (2014/08/26). Also, **Figure 5** shows the visualization results of the depth values of significant earthquakes with over 2.5 magnitude values in one week of January 2023. We can observe that there is a point where deep earthquakes had happened through the whole period (eg. New Zealand, Jan 7th, 9th, 10th and 13th).

In this case, the time-series query expression as a new time-series stream will be created by the depth value of earthquake by 6 basic fun2ctions defined in Section 3 to express the query-time-series-stream for time-series semantic computing. In this case, the time-interval is set as 1 week, and the time-granularity is set as 1 day.

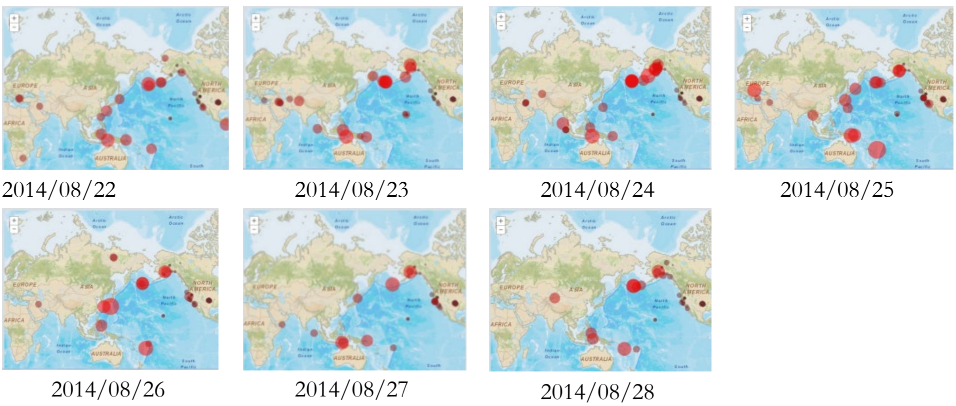


Figure 4: Time-series change of geographical distribution of the depth values of significant earthquakes with over 2.5 magnitude values, which occurred around the world during the period from Aug. 23rd to Aug. 28th, 2014

Source: own.

The following is an example of query creation and time-series-context settings for the analysis of significant earthquake and prediction with time-series semantic computing.

Input data for analysis (IRD) = time-series values of earthquake depth in two points

- Depth value of earthquake in Alaska
- Depth value of earthquake in New Zealand

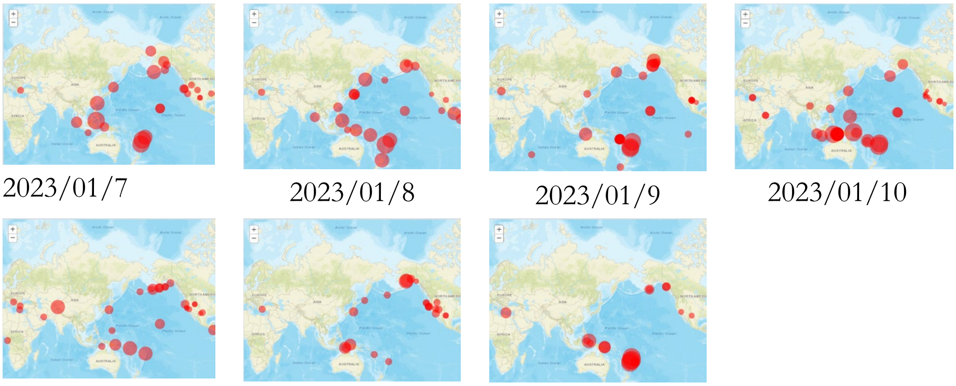


Figure 5: Time-series change of geographical distribution of the depth values of significant earthquakes with over 2.5 magnitude values, which occurred around the world during the period from Jan. 7th to Jan. 13th, 2023
Source: own.

Input data for prediction (ITD) = time-series values of earthquake depth in a target point

- Depth value of earthquake in Japan

As for the 6 key elements to express time-series-context, we can apply the followings.

6 Key elements for express time-series-context are:

- Original time-granularity (OG) = daily
- Target timing-granularity (TG) = peaks of earthquake depth
- Feature extraction method (FEM) = time point of peaks
- Focusing time-interval (FW) = from first peak to the last peak 3 or more peaks that matched condition
- Differential computing method (DCM) = ratio computing function for, number of days between the selected adjacent peaks, by applying average, difference, and other functions
- Pivot extraction method on ITD (PEM) = most recent 2 or more peaks that matched condition

4.2 Case II: Deforestation analysis with time-series semantic computing on 5D World Map System

This case shows the analysis of the time-series difference extraction on deforestation in Mae Wong National Park in Thailand (**Figure 6**) during the period from 2003 to 2013, where the deforestation has heavily happened previously, and large-scale of restoration is deployed currently. **Figure 7** shows the examples of original Landsat 7 and 8 satellite images of this area.

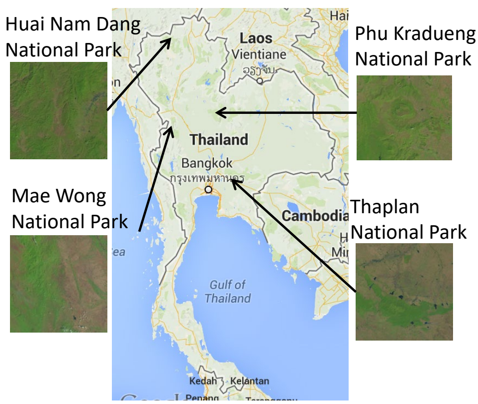


Figure 6: Four important national parks to analyze deforestation in Thailand

Source: own.

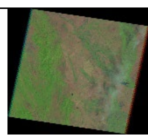
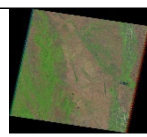
2003, Jan.	2004, Feb.	2005, Feb.
		

Figure 7: Examples of original Landsat satellite images of Mae Wong

Source: own.

Figure 8 shows the result images of pre-processing for Landsat satellite images of Mae Wong from 2003 to 2013. To detect the change in the same season (dry season, less cloud in Thailand), the images of January to Februaty are collected. The pre-processing for the original images starts from rotating, via position adjustment, trimming (calibration), and ends by color-contrast adjustment.

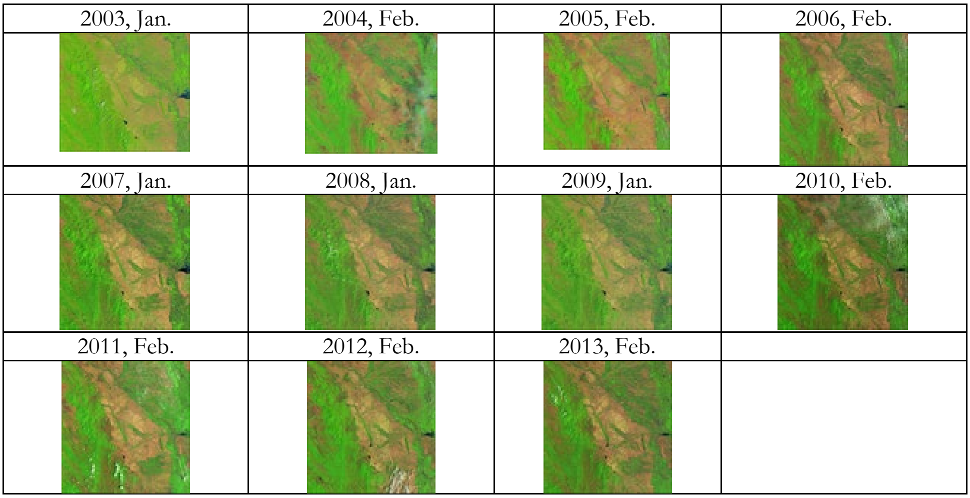


Figure 8: The pre-processed images of Landsat satellite images of Mae Wong area in Thailand from 2003 to 2013

Source: own.

Figure 9 shows the difference extraction results. The number of color clustering was set as 4 clusters. The focused colors are bright-green and dark green, which means forest area. Retreated parts are represented in orange color, and advanced parts are represented in blue color. The results show that the retreated area of green increased much from 2003 to 2004, but not so much from 2004 to 2005. From 2005 to 2007, the advanced area is observed, but from 2007, the retreated area can be observed again. From 2007 to 2013, the retreated area gradually decreased.

These results might show a success of the forest restoration policy and activities, though the deeper analysis with forest specialists is needed. We need to examine the details to judge if these results mean the speed of deforestation is reduced year by year.

As shown in **Figure 10** and **Figure 11**, the original satellite images with geo information and the difference-images can be mapped onto 5D World Map System and visualized with other data such as sensor data of weather and statistical data about deforestation around the world. This visualization enables users to understand the complicated relations among various elements of environmental phenomena intuitively.

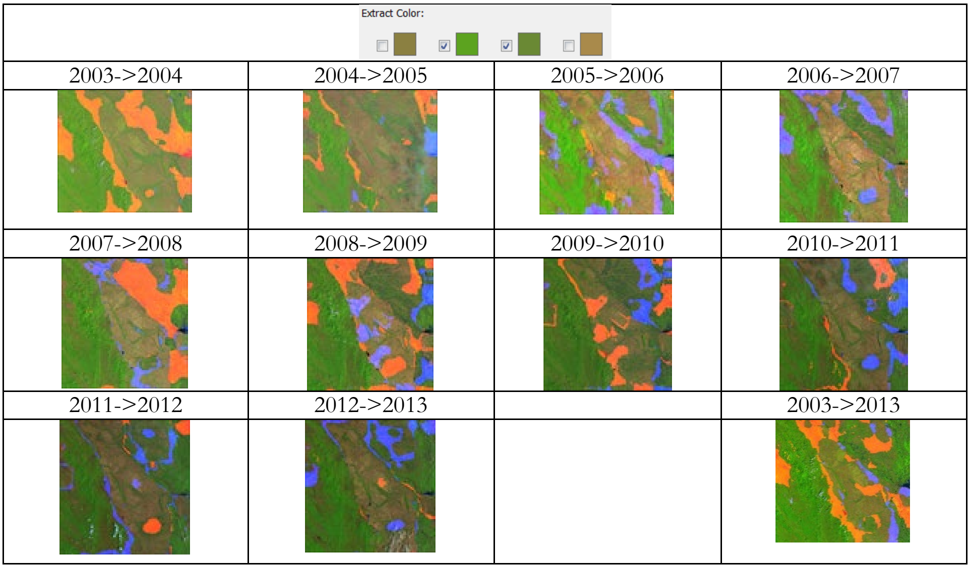


Figure 9: Results of difference extraction and difference-image creation (The number of clustering is 4. The focused color is bright-green and dark green, which means forest area. Retreated parts are shown in orange, and advanced parts are shown in blue.)

Source: own.

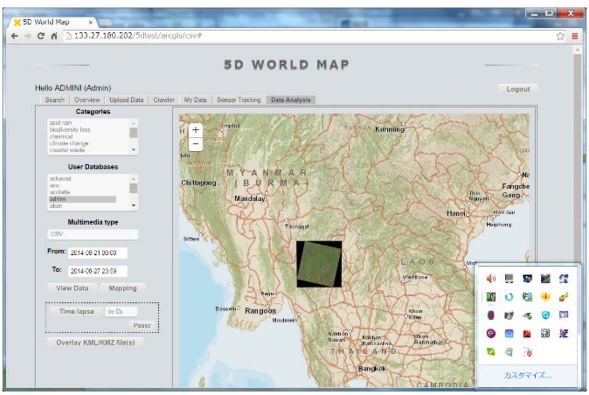


Figure 10: Mapping of an original satellite image with geo information converted as a KML file

Source: own.

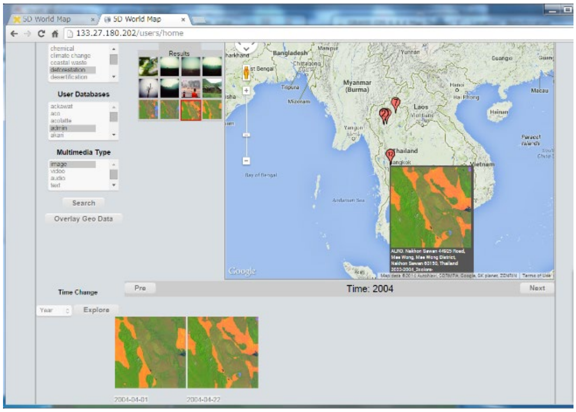


Figure 11: Mapping of the difference-images extracted by SIDE onto Mae Wong area
Source: own.

In this case, to analyze and predict the time-series stream of deforestation and restoration (recovery) of forest in national parks, the time-series query expression as a new time-series stream will be created by the area size of deforestation (retreated area and advanced area) by 6 basic functions defined in Section 3 to express the query-time-series-stream. In this case, the time-interval is set as 10 years, and the time-granularity in time-series-stream is set as 1 year.

The following is an example of query creation and time-series-context settings for the analysis of deforestation and prediction with time-series semantic computing.

Input data for analysis (IRD) = time-series values of area-size of deforestation in Mae Wong in Thailand

- Area-size of deforestation in Mae Wong National Park

Input data for prediction (ITD) = time-series values of area-size of deforestation in target points (other national parks in Thailand)

- Area-size of deforestation in Huai Nam Dang National Park
- Area-size of deforestation in Phu Kradueng National Park
- Area-size of deforestation in Thaplan National Park

As for the 6 key elements to express time-series-context, we can apply the followings.

6 Key elements for express time-series-context are:

- Original time-granularity (OG) = daily
- Target timing-granularity (TG) = peaks of deforestation
- Feature extraction method (FEM) = time point of peaks
- Focusing time-interval (FW) = from first peak to the last peak 3 or more peaks that matched condition
- Differential computing method (DCM) = ratio computing function for, number of days between the selected adjacent peaks, by applying average, difference, and other functions
- Pivot extraction method on ITD (PEM) = most recent 2 or more peaks that matched condition

5 Conclusion

We have presented a new concept of "*Time-series Semantic Computing*" for realizing global and temporal environmental analysis. The main feature of this system is to realize semantic time-series analysis in a multiple dimensional semantic space. This space is created for dynamically computing semantic relations between time-series data resources in different places and time. We have applied this method to time-series data resources in 5D World Map.

This system realizes a remote, interactive and real-time environmental research exchange among multiple and different remote spots in different areas. We have created a semantic-space for time-series analysis in environmental phenomena with multiple-dimensional axes along the time-axis. As the first step, this space is expandable to multiple spots to analyze and compare their time-series data in the global scope for environmental phenomena. We mapped them onto 5-Dimensional World Map System to make time-series semantic interpretations in those spots, as an international collaborative platform for environment analysis, to realize spatio-temporal and semantic interpretations.

As our future work, we will extend the *Time-series Semantic Computing*" realized onto 5-Dimensional World Map System to an international and collaborative research and education system for realizing mutual understanding and global knowledge-sharing on environmental issues in the world-wide scope.

Acknowledgement

We would like to appreciate "5D World Map System Project" members for their significant discussions and experimental studies. We also greatly appreciate Dr. Petchporn Chawakitchareon and and Dr. Sompop Rungsup for their active and collaborative research activities in environmental analysis.

References

[1] Yasushi Kiyoki and Saeko Ishihara: "A Semantic Search Space Integration Method for Meta-level Knowledge Acquisition from Heterogeneous Databases," Information Modeling and Knowledge Bases (IOS Press), Vol. 14, pp.86-103, May 2002.

[2] Yasushi Kiyoki, Xing Chen, "A Semantic Associative Computation Method for Automatic Decorative-Multimedia Creation with "Kansei" Information" (Invited Paper), The Sixth Asia-Pacific Conferences on Conceptual Modelling (APCCM 2009), 9 pages, January 20-23, 2009.

[3] Yasushi Kiyoki, Xing Chen, Shiori Sasaki, Chawan Koopipat, "A Globally-Integrated Environmental Analysis and Visualization System with Multi-Spectral & Semantic Computing in "Multi-Dimensional World Map", Information Modelling and Knowledge Bases XXVIII, pp.106-122,2017

[4] Yasushi Kiyoki, Shiori Sasaki, Nhung Nguyen Trang, Nguyen Thi Ngoc Diep, "Cross-cultural Multimedia Computing with Impression-based Semantic Spaces," Conceptual Modelling and Its Theoretical Foundations, Lecture Notes in Computer Science, Springer, pp.316-328, March 2012.

[5] Yasushi Kiyoki: "A "Kansei: Multimedia Computing System for Environmental Analysis and Cross-Cultural Communication," 7th IEEE International Conference on Semantic Computing, keynote speech, Sept. 2013.

[6] Shiori Sasaki, Yusuke Takahashi, Yasushi Kiyoki: "The 4D World Map System with Semantic and Spatiotemporal Analyzers," Information Modelling and Knowledge Bases, Vol.XXI, IOS Press, 18 pages, 2010.

[7] Totok Suhardijanto, Yasushi Kiyoki, Ali Ridho Barakbah: "A Term-based Cross-Cultural Computing System for Cultural Semantics Analysis with Phonological-Semantic Vector Spaces," Information Modelling and Knowledge Bases XXIII, pp.20-38, IOS Press, 2012.

[8] Chalisa Veesommai, Yasushi Kiyoki, Shiori Sasaki and Petchporn Chawakitchareon, "Wide-Area River-Water Quality Analysis and Visualization with 5D World Map System", Information Modelling and Knowledge Bases, Vol. XXVII, pp.31-41, 2016.

[9] Chalisa Veesommai, Yasushi Kiyoki, "Spatial Dynamics of The Global Water Quality Analysis System with Semantic-Ordering Functions". Information Modelling and Knowledge Bases, Vol. XXIX, 2018.

[10] Yasushi Kiyoki, Asako Uraki, Chalisa Veesommai, "A Seawater-Quality Analysis Semantic-Space in Hawaii-Islands with Multi-Dimensional World Map System", 18th International Electronics Symposium (IES2016), Bali, Indonesia, September 29-30, 2016.

[11] Yasushi Kiyoki, Petchporn Chawakitchareon, Sompop Rungsupa, Xing Chen, Kittiya Samlansin, "A Global & Environmental Coral Analysis System with SPA-Based Semantic Computing for Integrating and Visualizing Ocean-Phenomena with "5-Dimensional World-

Map", INFORMATION MODELLING AND KNOWLEDGE BASES XXXII, Frontiers in Artificial Intelligence and Applications 333, IOS Press, pp. 76 – 91, Dec 2020.

[12] Shiori Sasaki and Yasushi Kiyoki, "Real-time Sensing, Processing and Actuation Functions of 5D World Map System: A Collaborative Knowledge Sharing System for Environmental Analysis", Information Modelling and Knowledge Bases, Vol. XXVIII, IOS Press, pp. 220-239, May 2016.

[13] Yasushi Kiyoki, Xing Chen, Chalisa Veesommai, Shiori Sasaki, Asako Uraki, Chawan Koopipat, Petchporn Chawakitchareon and Aran Hansuebsai, "An Environmental-Semantic Computing System for Coral-Analysis in Water-Quality and Multi-Spectral Image Spaces with "Multi-Dimensional World Map", Information Modelling and Knowledge Bases, Vol. XXVIII, 20 pages, March 2018.

[14] Sompop Rungsupa, Petchporn Chawakitchareon, Aran Hansuebsai, Shiori Sasaki and Yasushi Kiyoki, "Photographic Assessment of Coral Stress: Effect of Low Salinity to Acropora sp. Goniopora sp. and Pavona sp. at Sichang Island, Thailand", Information Modelling and Knowledge Bases, Vol. XXVIII, 20 pages, March 2018.