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Geo-Spatial Big Data Analysis: An Overview

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Abstract: Advance increasing interest in large-scale, high-resolution, real-time geographic information system (GIS) applications and spatial big data processing, traditional GIS are not efficient enough to handle due to limited computational capabilities. Geospatial analytics in big data needed new approaches that are flexible, non-parametric and should be able for dynamic modeling with non-linear processes. Compared to general big data, the special thing of geographical big data is Spatiotemporal Association Analysis (SAA) for scrutinizing the geographical big data. This analysis wraps of some vital elements of geometrical relations, statistical correlations, and semantics relations for effective decisive and predictive measurements based solutions. The gist and aim of this paper is to study and review the Spatiotemporal Association Analysis (SAA) in three aspects such as measurement (observation) adjustment of geometrical quantities, human spatial behavior analysis with trajectories, data assimilation of physical models and various observations.

Keywords: *Geospatial Big Data; GIS; Spatiotemporal Analysis; Geometric Quantities; Human Behavior Trajectories; Spatiotemporal Statistics; Data Assimilation*

I. INTRODUCTION

In the last few years' big data has getting great prominence at international arena and gaining momentum at academies, industries and other institutions. The concept of big data emerged in the scientific fraternity in the mid 1990s and become the focal point during 2008-2010. Big data including geospatial big data has so much to offer to the society in meteorology, diagnostics, disaster management, logistics, and so on.

As per the available data 80% of the same is geo referenced i.e. which shows the importance of geospatial big data handling [1]. Geospatial data or spatial data is nothing but the information of a physical object, defined by values in a co-ordinate system. In common man's language, geospatial represents the location, size and shape of an object on earth such as a country, rivers, towns or skyscrapers.

Geospatial technology refers all the technology use to gather, manipulate and store geographic information. Geographic Information System (GIS) is one form of geospatial technology. Due to its technical limitations, traditional GIS are not efficient enough to handle the increasing interest in large scale, high resolution and real-time GIS applications and spatial big data processing.

The objectives of this paper is to review 1) collection of spatiotemporal data; 2) classification of spatial and spatiotemporal data; 3) classification on spatiotemporal relations; 4) three aspects of spatiotemporal association analysis; 5) tools of spatial and spatiotemporal analysis and conclusions to the paper.

II. SURVEY OF GEOSPATIAL BIG DATA

Yangming JIANG et al. [2] nominated a dynamic object oriented model which is regarded spatiotemporal class as a base class of four classes – ZeroTObject (ZTO), OneTObject(OTO), TwoTObject (TTO), ThreeTObject (TTHTO) where as ZTO is a temporal node, OTO is a temporal arc, TTO is a temporal polygon, and THTO is a temporal cube. This model is deployed to trigger changes in digital earth. ZHANG Ruiju et al. [3] nominated the spatiotemporal data model based on space-time composite model in which spatiotemporal object has a exclusive identifier irrespective of changes it goes through. The challenges in spatiotemporal data model are debated and a general object oriented spatiotemporal model is advocated by Bonan Li et al. [4]. Various approaches to representing changes of geographical phenomena for investigating and trailing the evolution of objects are discussed by Southeil Khaddaj et al. [5].

Cheng et al. [6] reviews the recent dynamic trends in spatiotemporal big data mining research including spatiotemporal autocorrelation, space-time forecasting and prediction, space-time clustering, and also space-time visualization. Shekhar et al. [7] provide the state of the art review of spatial big data mining research. Shekhar et al [8] scrutinized various spatial pattern families focused on the spatial data's exclusive characteristics. Aggarwal et al. [9] describes spatial and spatiotemporal outlier detection techniques. Zhou et al. [10] evaluate spatial and spatiotemporal change detection research from an interdisciplinary view. An analytical study on spatiotemporal clustering research is done by kisilevich et al. [11].

As per Duda.R et al. [12] studies, knowledge discovery methods have been employed to analyze large sports data recently and it indicates decision trees, support vector machines or neural networks method of classification analysis are applicable. Rathod et al. [13] introduced a novel approach by fuzzy inference system with distinct characteristics which is extracted from key frames. Xu et al. [14] proposed a semantic method by bridging semantically-valuable human expert knowledge to video content to automatically bring events with semantic information. Likewise, Yue et al. [15] presented a meticulous spatial model which can predict near-future events by learning semantically-meaningful representations.

Ranga raju et al. [16] reviewed a major spatial data algorithms including spatial autoregressive model (SAR), markov random field classifiers, Gaussian Process (GP) learning by comprehensively analyzing computational and I/O challenges. Momoulis et al. [17] reviewed mining spatiotemporal big data by collecting the locations at corresponding relative timestamps and proposed a top-down pattern mining method, which is far better than typical bottom-up approach.

In this literature survey many geospatial big data analysis based on different mining techniques have been discussed and each analysis has its own advantages and limitations

In this analysis of geospatial big data mining technique begins with the collection of spatiotemporal data and continue to explore classification of spatial and spatiotemporal data, classification on spatiotemporal relations, three aspects of spatiotemporal association analysis and tools used for spatial and spatiotemporal big data analysis.

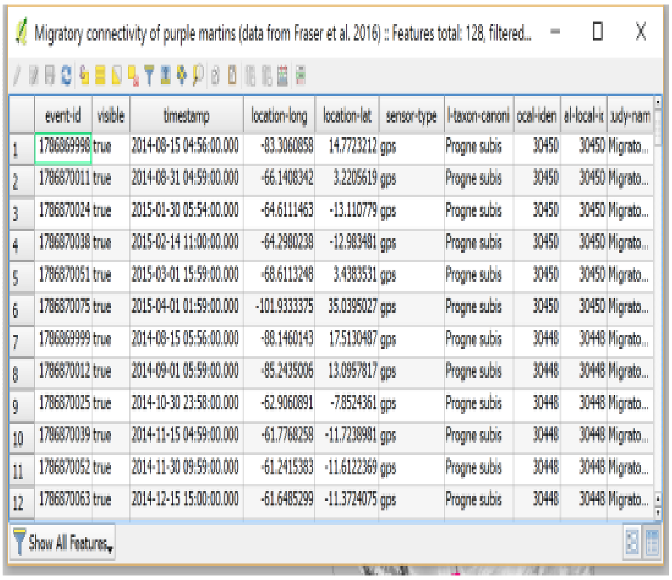
III. GEOSPATIAL BIG DATA ANALYSIS

A. Spatiotemporal big data Analysis

Spatiotemporal data mining for geospatial big data deals with the process of exploring potentially new useful patterns from vast spatiotemporal databases. It has broad application domains including ecosystems and environmental management, logistics, medical science and meteorology.

B. Spatiotemporal Data collection

In real world, the attributes of data mostly depends on location and time. The data which is related to spatial (location) and temporal (time) information is called as spatiotemporal data. Two most frequently seen spatiotemporal data are (i) ID-based spatiotemporal data (non-spatial data) collected from GPS [fig.1] and (ii) location-based data (spatial data) collected from sensors [fig.2].



Migratory connectivity of purple martins (data from Fraser et al. 2016) :: Features total: 128, filtered...

	event-id	visible	timestamp	location-long	location-lat	sensor-type	l-taxon-canoni	ocal-iden	al-local-i	udy-nam
1	1786869998	true	2014-08-15 04:56:00.000	-83.3060858	14.7723212	gps	Progne subis	30450	30450	Migrato...
2	1786870011	true	2014-08-31 04:59:00.000	-66.1408342	3.2205619	gps	Progne subis	30450	30450	Migrato...
3	1786870024	true	2015-01-30 05:54:00.000	-64.6111463	-13.110779	gps	Progne subis	30450	30450	Migrato...
4	1786870038	true	2015-02-14 11:00:00.000	-64.2980238	-12.983481	gps	Progne subis	30450	30450	Migrato...
5	1786870051	true	2015-03-01 15:59:00.000	-68.6113248	3.4383531	gps	Progne subis	30450	30450	Migrato...
6	1786870075	true	2015-04-01 01:59:00.000	-101.9333375	35.0395027	gps	Progne subis	30450	30450	Migrato...
7	1786869999	true	2014-08-15 05:56:00.000	-88.1460143	17.5130487	gps	Progne subis	30448	30448	Migrato...
8	1786870012	true	2014-09-01 05:59:00.000	-85.2435006	13.0957817	gps	Progne subis	30448	30448	Migrato...
9	1786870025	true	2014-10-30 23:58:00.000	-62.9060891	-7.8524361	gps	Progne subis	30448	30448	Migrato...
10	1786870039	true	2014-11-15 04:59:00.000	-61.7768258	-11.7238981	gps	Progne subis	30448	30448	Migrato...
11	1786870052	true	2014-11-30 09:59:00.000	-61.2415383	-11.6122369	gps	Progne subis	30448	30448	Migrato...
12	1786870063	true	2014-12-15 15:00:00.000	-61.6485299	-11.3724075	gps	Progne subis	30448	30448	Migrato...

Show All Features

Fig. 1: A sample of real moving object data showing non-constant sampling rate

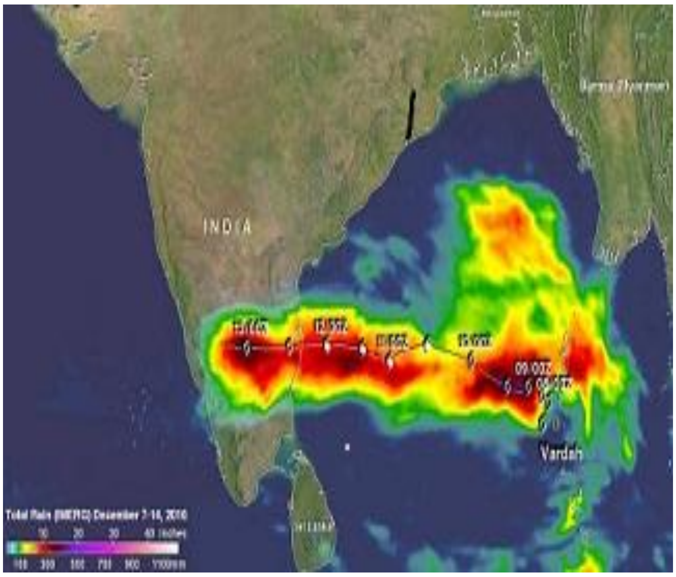


Fig. 2: Rainfall totals were estimated from Dec.7 through 14, 2016 and about 500 mm (19.7 inches) were analyzed in the area west of the Andaman Islands where Vardah formed Credits: NASA/JAXA, Hal Pierce

An ID-based spatiotemporal data is trajectory as the tracking device is attached to a moving object. For example, cell phone data enable us to track an individual's movements. If there are trajectories of 'n' moving object {O1,O2,…,On}, each trajectory is represented as a sequence of points (x1,y1,tm), (x2,y2,tm),…, (xn,yn,tm) where (xi,yi) is a longitude and latitude and 'ti' is the time when location (xi,yi) is recorded.

When a temporal data is collected from a fixed location, it is called as location based spatiotemporal data [18]. For example, sensors fixed at different locations to track rainfall and humidity etc. There are a set of related properties at location (x,y) at time 't'. F(x, y, t, p) is used to find out the value of property 'p' at location (x,y) at time 't'.

C. Classifications of spatial and spatiotemporal data

One important feature of spatiotemporal analysis is data inputs, which are little baffling as it includes discrete representations of continuous space and time. Table 1 indicates the classifications of different spatial and spatiotemporal data models[19]. Spatial data can be divided into three models i.e. the object model, the field model and the spatial network model.

Object model is called entity based or feature based as well. Individual objects are represented in a detailed and clear manner using their geometric counterpart. Primitive spatial data objects are point, lines and polygons located in a spatial reference frame. These geometric primitives indicated static locations and spatial extents of geographic phenomena in terms of XY coordinates.

In Field model, the underlying (geographic) space is partitioned into cells that cover it entirely. Spatial objects are embedded into the space and are described and manipulated in terms of the cells they intersect. Usually the partition is composed of polygonal units of equal size (fixed or regular grid: raster). It transforms space partition (example: raster) to attribute domain (example: height, rainfall, temperature).

A spatial network model contains graphs. A graph G = (V, E) where V = a finite set of vertices, E = a set of edges E between vertices in V. The space in which the system is embedded acts as a constraint on the design of the network. In a spatio-temporal setting, we can represent this constraint as the speed with which one node can communicate with another. In general, a spatio-temporal path from node v0 may visit several distinct vertices before reaching its destination node. A spatio-temporal path consisting of n≥0 hops, starting with origin node v0 at timestamp t1, is described as the sequence of n+1 pairs

$$\langle (v0,t1), (v1,t'arr\ 1), (v2,t'arr\ 2),\ldots,(vj,t'arr\ n)\rangle \quad (1)$$

Where vj denotes the jth node visited on the path and t'arr n denotes the time at which the path reached node vj.

TABLE 1 : TAXONOMY OF SPATIAL AND SPATIOTEMPORAL DATA

Spatial Data		Temporal Snapshots	Change	Event/Process
	point(s)	point trajectories	Translation or acceleration	spatial/spatiotemporal point process: Poisson Process, or Cluster point pattern
object model	line(s)	line trajectories	Translation/ rotation/ expansion or contraction	line process
	polygon(s)	polygon trajectories	Translation/ rotation/ expansion or contraction/ mutation	flat process

field model	regular irregular	raster time series	change over raster snapshots	cellular automation
spatial network	Graph	spatiotemporal network: 1. time expanded graph, time aggregated graph; 2. network flows	Insertion or deletion of vertices and edges	1. random geometric graph; 2. hyperbolic geometric graph 3.exponential random graph model 4. Percolation theory

IV. CLASSIFICATIONS ON SPATIOTEMPORAL RELATIONSHIPS

Spatiotemporal data mining in geospatial big data refers to the extraction of knowledge and spatiotemporal relationships that are not stored vaguely in spatiotemporal databases. It's an upcoming concept dedicated to the development of computational techniques for analyzing huge amount of spatiotemporal databases. It presents lot of challenges due to compound geographic domains and mapping of all data values into spatial and temporal frameworks. The spatiotemporal relationship is categorized into geometrical relations, statistical relations and semantic relations.

A. Geometric relations

Spatiotemporal objects capture spatial and temporal aspects of data simultaneously and deal with geometry changes over time. Object id, geometry, time and attributes are the four tuple which represents it. Recording a spatial object at a time point results a snapshot of it.

Modeling spatiotemporal applications is a compound task which involves detailed and complicated issues such as representation of geometry of objects as well as its change in time and spatial attributes which change their values depends on specific locations in time periods.

Topology give a detailed account about spatial relationships like intersects touches, etc between spatial objects. The spatial objects maybe point, polygon or line. Various types of spatiotemporal topologies relationships between two objects[19] are shown in table 2.

TABLE 2: TAXONOMY OF SPATIOTEMPORAL DATA RELATIONS

Spatial Data		Temporal Snapshots	Change	Event/ Process
object model	point(s), line(s), polygon(s)	Space- time predicates , trajectory distance , spatiotemporal correlation	1.Translation or acceleration 2. (for line and polygon) Translation/ rotation/ expansion or contraction / mutation	Space-time co-variance diagram, spatio-temporal coupling
field model	Regular tessellation, Irregular tessellation	map algebra temporal correlation, Euclidean plane, spatial distribution	Change over snapshots in possible operations on fields such as local, focal and zonal	Cellular automation
spatial network	Graph	Lagrangian path, Hamiltonian mechanics , temporal centrality , network flow	change in centrality, connectivity, closeness, distance	Space-time coupling of network events

B. Statistical relations

The approach implicit spatiotemporal relationship is to materialize the relationship into traditional data input columns and apply classical big data mining techniques. But it can result in loss of information. The spatial and temporal vagueness creates faster modeling and processing difficulty in spatial and spatiotemporal big data mining. The better approach to capture implicit spatial and spatiotemporal relationship is to develop statistics techniques to incorporate spatial and temporal information into the big data mining process.

Spatiotemporal statistics is the combination of spatial statistics with temporal statistics (time series analysis) dynamic models [19]. The common statistics for different spatiotemporal data analysis includes spatial time series, spatiotemporal point process and time series of lattice (areal) data summarizes in table 3.

Spatiotemporal time series is a time series of data points indexed in time sequence and time series are frequently plotted via line charts. Time series forecasting is the use of model to predict future values based on periodically obtained values. The spatiotemporal point process generalizes the spatial point process by containing the factor of time. Along with spatial point process there is also spatiotemporal poison process, cox process and cluster process. Apart from this, spatiotemporal K function and spatiotemporal scan statistics also there. Time series of areal data is the autocorrelation of spatial and temporal. There are other spatiotemporal statistics like empirical orthogonal functions (EOF) analysis, canonical-correlation analysis (CCA), and spatiotemporal models for data assimilation [19].

TABLE 3: TAXONOMY OF SPATIOTEMPORAL STATISTICS

Spatial model		**Spatiotemporal Statistics**
Object model	Points	Statistics for spatial time series (krigning, kalman factor etc.) Spatiotemporal Point Process (poission process, cox process, cluster process etc)
Field model	Regular, irregular	Statistics for raster time series (EOF analysis, CCA analysis, data assimilation etc)

C. Semantic relations

The well known understanding between human beings and computer systems exchanging information will make any communication concept runaway success. It is essential to evaluate the semantic similarity between these concepts to obtain a sufficient level of semantic interoperability. So many approaches to assess the semantic similarity between concepts are there and mostly such calculations of semantic distances are based on taxonomic and patronymic relations. It is significant to an account for their spatial relation in the calculation process while evaluating semantic similarity between geospatial concepts. All geospatial objects have a position in space linking with some spatial reference system and consequently a spatial relation to each other on the conceptual level, spatial relations are cantered characteristics. Gärdenfors idea[20] of conceptual space has to be applied—a set of quality dimensions within a geometric structure for formal representation of concept and their calculations of their semantic similarities. This representation depends on the foundation of cognitive semantics, confirming that meanings are mappings from expressions to conceptual structures.

Concepts can be summarized by their properties or relations to other concepts. The properties in a conceptual space are represented by the dimensions or domains. A property can be formalized by a dimension with a value - dimension (concept) = value, whereas the value of dimension Dn = {(d1, d2…, dn) | d ∈ D}, the value of concept Cn={(c1, c2…, cn) | c ∈ C}) and the value is defined within a specific range[20]. It is very much essential to use natural-language temperature to capture the semantics of geo-objects with spatial relations.

V. Aspects of Spatiotemporal Analysis

Spatiotemporal data analysis for geospatial big data deals with the process of exploring potentially new useful patterns from vast spatiotemporal databases. It has broad application domains including ecosystems and environment management, logistics, medical science and meteorology. Measurement adjustments of geometrical quantities, human behavior analysis with trajectories and data assimilation of physical models are the three aspects of spatiotemporal data analysis, from which the spatiotemporal big data analysis may be largely derived.

A. *Measurement adjustment of geometrical quantities*

In mathematics, space and time are shaped into geometric quantities. Time is measured by motion frequency of objects. Employing various surveying instruments, phenomena of physical and human geography are monitored for a large amount of geo referenced data in contemporary world. In this digital era, topographic observation and geographical phenomena sensing are digitally recorded in the computer and geometrical relation analysis is given great importance in geographical big data analysis.

The components of geo-spatial data sets have to be handled differently in the time of spatial adjustment; the object breaks down the primary component of the data set into individual layers i.e. point layer, poly lines layer, and polygon layer. This is used for determining geometrical quantitative difference. The difference determination includes the process of extracting the geo-data's spatial geometry and determining the geometry relationships of components be based on the particular geo-data source.

To disintegrate geo-data from any source into primitive objects/elements, spatial validation and spatial reverse engineering (SRE) are applied. The strength and goals of SRE are to analyses a data set, to find out data components, to identify the inter relationship of data components, and to generate representation of the data in another form or at a higher level of distractions. SRE assists to return to a less complex or more primitive state or stage of the spatial data geometry. The resultant algorithm has to execute poly lines and polygons corrections according to the geometrical spatial difference. This object examines different spatial primitives which have been adjusted and builds them into components of spatial meaning and these are later combined during topology building.

B. *Human behaviour analysis with trajectories*

On the arrival of the internet and mobile devices, the trajectories of mobile objects are captured. The trajectory is digitally illustrated by a sequence of space – time coordinate points (x, y, t). For human beings, spatial behavior of individuals or group activities can be explored by trajectories. Generally time geography and spatial cognition are considered as the scientific foundation of human geographical data analysis. Human behavior analyses involve detecting, tracking and understanding people's behavior.

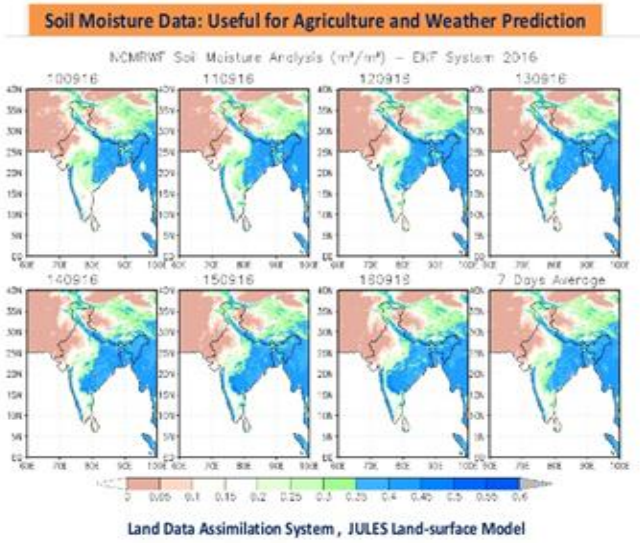


Fig 4: NCMRWF Soil Moisture analysis (m^3/m^3) during onset phase of Monsoon-2016

To segment these traces into trajectories that daily mobility pattern of each individual can be identified, using by basic algorithm. It is suggested to extract trajectory and stop [21]. Let Xk denote a set of sequential traces of user k such that Xk= {xk(1), xk(2), xk(3), ...} where xk(i) is a position i of user k. A trajectory can then be obtained by segmenting Xk with the spatial threshold S. If, in case a distance between adjacent position is greater than the threshold that is distance(xk(i),xk(i + 1)) > S, then the early position xk(i) becomes the end position of the last trajectory while the later position xk(i+1) becomes the starting position of the next trajectory. Once the trajectories are found out, a stop can be indicated as an event during which the user stays in a specific location for a long period of time more than enough. As each position i contains the location and the timestamp(t), that is xk(i) = (lat(i), long(i), t(i)) whereas lat(i) is latitude position, long(i) is longitude position , extraction of a stop depends on time and space. A stop is thus considered as a sequence of positions {x (j), x (j + 1), x (j + 3), ..., x(j + m)} where the distance between any adjoining positions is less than a spatial threshold Sth i.e., distance (x(j), x(j + 1)) < Sth, and time spent within the location is greater than a time threshold Tth i.e., t(m) − t(j) > Tth. After stops have been found out, work location of each user is then assumed as a most frequent stop during the day hours. The information about work location enables us to conclude the mobility choices of the users, and track activity patterns throughout the day. The daily mobility of a person represents in Fig 3.

Fig 3: Daily mobility pattern of an individual illustrated by a sequence of space – time Coordinate points (x, y, t) - Credit: hkeita / Shutterstock

C. *Data assimilation of physical models*

A significant building block of advanced decision support tools is data assimilation. Data assimilation can be explained as the application of recursive Bayesian estimation [22] to combine current and past data in a comprehensive dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields. Data assimilation intents to deploy both our knowledge of physical processes as embodied in a numerical process model, and information that can be obtained from observations, to bring out an improved, continuous system state estimate in space and time. When carry out in near-real time, data assimilation can objectively offers decision makers with well timed information, as well as bestows superior initializations for short term scenario predictions.

Fig. 4 shows an example to predict the soil moisture using land data assimilation system. For analyzing the similarities of soil wetness (top layer soil moisture analysis) with observed satellite soil moisture products, it is usual practice to express soil moisture in volumetric units i.e. in volumetric fraction of soil water in a given soil depth. Soil wetness analysis (units: kg/m^2 or mm) is converted to volumetric soil moisture (units: m^3/m^3) by using the formula:

$$\text{volumetric soil moisture} = \frac{\text{soil wetness}}{\rho_{water} \times \partial z} = 0.01 \times \text{Soil wetness} \quad (2)$$

(for ∂z = 100 mm for first soil level and the water density ρ_{water} =1000 kg/m^3) [22]

VI. TOOLS FOR SPATIAL AND SPATIOTEMPORAL ANALYSIS

This topic deals with the currently existing spatial and spatiotemporal analysis tools, comprising geographic information system (GIS) software's, spatial and spatiotemporal statistical tools, spatial database management systems and spatial big data platforms as well.

GIS software's: The most popular commercial GIS software's for working with maps and geographical information currently is ArcGIS [23]. Tracking analyst is an extension to assist visualization and analysis for spatiotemporal data. Widely used open source GIS software is QGIS [24].

Spatial statistical tools: R tool offers multiple packages for spatial and spatiotemporal statistics analysis, like spatstat for point pattern analysis, gstat and geoR for geostatistics, spdep for local data analysis [25]. Mapping toolbox and other spatial statistical toolboxes are offered by Matlab [26]. Spatial statistics like KRIGE2D procedure for kringing, SIM2D procedure for Gaussian random field, SPP procedure for spatial point pattern and variogram procedure for variograms is getting supported by statistical analysis system (SAS) [27].

Spatial database management system: Lot of commercial database extending support to spatial data's like oracle spatial [28] and DB2 spatial extender [29]. PostGIS[30] which is an extension to postgres, a mostly used open source spatial database management system.

Spatial big data platform: The spatial big data from mobile phone location data, vehicle GPS trajectories and remote sensing imagery are beyond the potentiality of traditional spatial database management system. It requires new platforms to assist measurable spatial analysis. Latest spatial big data platforms comprise ESRI GIS on Hadoop [31], Hadoop GIS [32], and spatial Hadoop [33].

VII. FUTURE CHALLENGES

Recent advances in computer science makes spatio temporal data even bigger, in addition large scale data generated by organizations, institutions and social media outlets is proving to be of immense value in disaster mapping and national security applications. Spatial computations need to be transformed to meet the challenges post by big spatio temporal data. NASA generates about 5TB of data per day and Google generates about 25PB of data per day. Significant portion of it is spatio temporal data. The rate at which spatio temporal data is being generated exceeds our ability to organize and analyze them which throws I/O challenges posed the big spatial data.

CONCLUSION

As lightening development happens in the field of computer and communication technology, the human – machine – environment system is witnessing overwhelming observation by the space-air-and ground based sensor digital networks.

This study reviews the collection of data for spatiotemporal big data mining, classifications of spatial temporal data. This study also illustrated the classifications on spatiotemporal relations such as geometrical relations in space and time, spatiotemporal correlations in statistics and space – time relations in semantics. Furthermore this study reviews the three kinds of spatiotemporal data analysis, i.e. measurement (observation) adjustment of geometrical quantities, human spatial behavior analysis with trajectories, data assimilation of physical models and various observations, from which spatiotemporal big data analysis may be largely derived.

Big spatiotemporal data mining is supporting key applications in the areas of immense value to the mankind. However in order to realize the full benefits of big spatial temporal data mining we have to overcome both computational and I/O challenges which throws us the window of opportunities to improve and innovate for serving mankind better.

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