GeoSmart Cities: Event-driven geoprocessing as enabler of smart cities

Manuel Garcia
ITC, University of Twente
The Netherlands
Email: m.g.garciaalvarez@utwente.nl

Javier Morales
ITC, University of Twente
The Netherlands
Email: j.morales@utwente.nl

***Abstract*—Smart cities are urban environments where sensor networks and geographic data become pervasive. Geographic Information plays a key role in understanding city dynamics, it provides relevant information to support decision making. Volume, velocity, and variety of data from sensor networks presents challenges to current geoprocessing paradigms. In this work, we highlight the role of geographic information from sensor networks in the context of smart cities, and describe three novel application cases under a framework that integrates event-driven architecture and geoprocessing services.**

I. Introduction

In smart cities, technology leverages city development in three major axes: management and planning, business and productivity, and citizens and quality of life. Six characteristics determine the smartness of a city: economy, people, governance, mobility, environment, and living. Smart economy makes a city competitive in a national and global context, hence a better service provider. Smart people and smart governance create social and human capital, and promotes a proactive participation of citizens in policy making. Smart mobility provides efficient and sustainable transportation services and ICT leads to a wired and connected city. Smart environment focuses on efforts for a sustainable management of natural resource. Finally, smart living provides a better quality of life by ensuring health, safety, housing, and entertainment [1].

Spatial and temporal characteristics of urban phenomena are key to the decision making process. The pervasiveness of sensor networks provides cities with spatial and temporal awareness to explore urban phenomena and their dynamics. Some examples include: human mobility, population distribution, social behaviors, and energy consumption patterns. Today's abundance of data calls for processing alternatives to benefit from big data analytics, to derive spatial and temporal characteristics of a phenomenon. Smart city's applications face limitations on processing and analyzing big amounts of data in a time-wise manner [2]. Geoprocessing of data streams inherits challenges from big data analysis: volume, velocity, variety, value, and veracity.

The Event Driven Architecture (EDA) provides a framework to build enhanced geoprocessing functionality. Events are a declarative mechanism to specify detectable conditions in a computer system. Event detection and processing provides control on how a system reacts to a particular situation. EDA can reduce data volume, administrate velocity of data production, and focus on relevant pieces of data to handle variety, while maintaining interoperability [3].

EDA and event processing adds desirable functionality to geoprocessing routines of data streams. Integration of geoprocessing services and EDA provides mechanisms to handle big data analytics challenges: volume, velocity, and variety. Moreover, it supports the development of 'smart' computational systems.

In this paper, we introduce the concepts of geo-smart cities and propose a system architecture to integrate EDA and geoprocessing. The specification of g-events is described as a mechanism to abstract relevant real world events. Finally, three application cases exemplify the use g-events in the context of smart city management.

II. Geo-Smart Cities

Smart cities provide the spatial and temporal context in which sensor networks play a key role. A high level of technology in smart cities makes sensors pervasive enough to capture the dynamics in the urban environment. Sensor networks allow the capture of big data related to citizens' activities, for instance: transportation choices [4], human movement [5], air quality monitoring [6], and deeper social behaviors [7], [8].

We define a **geo-smart city** as *an urban environment where authorities or citizens can exploit big data from sensor networks, to derive information, to improve decision making and boost citys efficiency, productivity, and collective-driven innovation.* In the geospatial context, this is translated into a demand for processing huge amounts of geo-data, distributing key information, and collecting relevant knowledge about city dynamics.

What we can sense through sensor networks depends on the nature of a phenomenon and the available sensor technology. Innovative solutions and applications to urban problems can result from understanding a Phenomenon of Interest (FoI), and the capabilities and data that different sensors can provide. Table I classifies sensors as: *fixed, mobile and human sensors*, and lists potential applications in the context of geo-smart cities. Fixed sensors (F) have a permanent location and usually are deployed to fulfill specific purposes, e.g. weather stations. Mobile sensors (M) are commonly built-in on other devices or are attached to mobile smart phones, clothes, goods/packages, and vehicles (cars, buses, UAVs). Human sensors (H) make use of third party platforms to report phenomena witnessed by users, through mechanisms such as social networks.

A *geo-smart city* relies on the existent communication infrastructures. The city of Santander (ES) has deployed a

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TABLE I. APPLICATIONS FOR SENSOR NETWORKS IN THE CONTEXT OF GEO-SMART CITIES.

SMARTNESS FOR	APPLICATION	DATA FROM	TYPE
ENVIRONMENT	Energy consumption profiles.	Power and gas meters in households and buildings.	F
	Concentration and distribution of pollutants.	Ad-hoc sensor network to monitor air quality.	F
		Human sensor reporting over the quality of water.	H
	Urban heat distribution caused by urban structures.	Temperature sensors, weather stations around the city.	F
		Temperature sensors attached to mobile phones.	M
	Energy efficient urban design.	Fixed sensors measuring: temperature, wind, sunlight.	F
MOBILITY	Use of public transportation services.	Smart card logs from travelers.	M
		Sensors reporting parking occupancy	F
	Traffic flow of vehicles.	Sensors attached to highway structures.	F
		Drivers reports, e.g. Waze	H
	Movement of goods and freight (supplies).	GPS devices in vehicles	M
		RFID for parcels	M
	Pedestrian's flow.	GPS devices	M
		Smart phones enabled with GPS capabilities	M
		Tweets with geotagging	H
	Use and load of telecommunication networks.	Location of digital identifiers when accessing devices, e.g. Wi-Fi hot spots loads and monitoring of data traffic.	F
		IP distribution and data transfers (bits/second). Cellphone networks usage.	M
LIVING	Presence of citizens in places of interest.	Check-ins and tagging in social networks.	H
	Livability	People reporting about living experience through Apps, e.g. Mappiness.	H
	Citizens living habits	Mobile phone logs. For instance, digital agendas.	M
	Citizen Health monitoring. Patients with chronic or terminal conditions. Remote diagnosis and emergency response.	Wearable sensors to monitor 'vital signs'. Use of biosensors.	M

network of over 2500 fixed and mobile sensors[1]. Citizens and local government efforts have provided Eindhoven city (NL) with air quality (fixed) sensors and human sensors report over waste production, crime incidents, among several others[2]. New sensor network deployments are promoted by government and business initiatives in Europe, or powered by the constantly increasing number of smart phone users. To leverage management in these cities we need to provide mechanisms to facilitate the exploitation of sensor data through which spatio-temporal context of urban phenomena enhance decision making.

Awareness, analytics and action are core functionalities demanded by smart city applications. Situational awareness is necessary to constantly monitor the city status and collect relevant data for an application. Analytics and processing are relevant due to the need to provide users with tools to perform data filtering, integration, correlation, interpolation, validation, etc., and to interpret big amounts of data by deriving relevant pieces of information. In order to make processing outputs useful, information needs to be translated into actions that have an effect on the city's infrastructure, and citizen's behavior, e. g. control traffic flows, and reduce energy consumption.

III. AN EVENT-DRIVEN GEOPROCESSING FRAMEWORK

We propose a framework for developing applications that exploit data from sensor networks. The framework depicts functionality and major components to develop geo-smart systems. A geo-smart system is a computational system that facilitates the processing and analysis of sensor data, and dissemination of relevant information. Major components of a geo-smart system correspond to the three core functionalities required in smart cities. A geo-smart system has the following characteristics:

- Applications are built on top of existing telecommunication infrastructures of a city.
- Sensor networks provide situational awareness via Sensor Observation Services (SOS).
- Analytics and processing capabilities are provided by loosely coupled components via distributed processing.
- Platform as a service (PaaS) allows a system to take advantage of high performance cloud computing.
- Applications (information consumers) use processing components through API's.
- Data processing is performed by an event-driven geoprocessing component that serves as a middleware.

Figure 1 presents a high level architecture of our framework for a geo-smart system. The middleware component integrates Event Driven Architecture, Complex Event Processing (CEP) and geoprocessing routines into an Event-driven Geoprocessing System (EGS). CEP provides the functionality of a rule-based system to embed expert knowledge, to administrate geoprocessing requests, and to perform spatio-temporal analytics.

[1]http://maps.smartsantander.eu
[2]http://goo.gl/YvDsVq

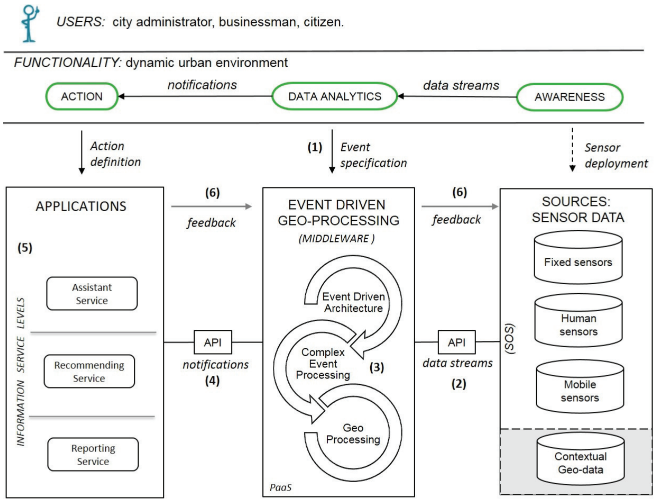

Fig. 1. Event-driven geoprocessing system architecture.

Geoprocessing routines and tools provide the analytical power to transform data streams into information streams requested by an application.

Typical users of a geo-smart system include administrators responsible for a dynamic urban environment. A dynamic Urban Environment (dUE) is *a geographic area for which a phenomenon is represented as a set of objects capable of reacting to events of interest*. dUEs may include, for instance, a stadium during a soccer match, or city districts where air pollution is monitored. Other users include businessmen developing smart city solutions and citizen communities proposing enhancements to their neighborhoods.

A typical user performs the following tasks:

- Identify a dynamic urban environment to be observed.
- Define a FoI, for which a deployment of sensors might be need it, e.g. volunteers downloading a smart-phone App to collect and transmit data.
- Identify Events of Interest (EoI) related with a FoI.
- Defines actions to affect city infrastructure or system behavior, when EoIs are detected.

An EGS aims to serve as a flexible and reusable component that fits and adapts to several applications. Typical users specify events for a dUE and application, noted as (1) in Figure 1. The Event Detector listens to sensor data streams waiting for an event to happen (2). Detected events trigger processing steps, including selection of spatial and temporal analysis for a particular data stream (3). Notifications and relevant information are sent through communication channels (4), and consumed by applications (5). Feedback mechanisms modify the behavior of the system (6).

A formalization mechanism specifies spatial and temporal characteristics of events under different contexts. For instance, events like traffic jams, poor air quality, and heavy rainfall are highly subjective and dependent on the spatial and temporal context of a particular dUE. Specific applications might require different abstractions, e.g. poor air quality does not necessary mean the same for a runner during a workout than for an environmentalist looking for effects on global warming. Abstraction is necessary to represent events in a computational system, and facilitate the exploitation of geographic information.

IV. G-EVENTS

In a general context, "events are real-world occurrences that unfold over space and time" [9]. This definition provides two fundamental characteristics of an event: its relation with a location or set of locations (space) and its intrinsic relation with time. Different approaches exist to formalize events. For instance, journalists report events following the five "W's" and one "H" principle: *(what, where, when, who, why and how)* [10]. What and who describe the nature of the event; where and when describe location and time; and why and how are used to describe relations between current and previous, or succeeding, events.

In the EDA and CEP context, an event is a notification of a change of state. Notifications that consider single occurrences of a change of state are called low level events. High level events are the result of the confluence of several low level events in an specific pattern of occurrence.

Specification provides a mechanism to abstract real-world situations and analyze urban phenomena. A mechanism to formalize events is presented in the following sections, as a starting step towards event-driven geoprocessing systems.

A. G-event Domains

Definition. G-event: An occurrence of a change of state associated to a phenomenon of interest, and which is related to a geographic location and a specific time.

G-events exhibit the following qualitative properties:

1) Relevance. A g-event is specified for an application and dUE.
2) Discrete. A g-event happens or does not happen.
3) Atomic. A g-event is not intended to describe all possible happenings of an event, but to abstract a single event of interest.
4) Finite. A g-event has a beginning and an end. An endless process is not a g-event.
5) Relative. G-events can be related to each other in terms of space, time, and causality. Simple g-events can be aggregated to produce a more complex g-event.

Axiom 1. *G-events* (e)*, are specified by five fundamental characteristics: phenomenon of interest, geographic space, time, recurrence, and causality. Low level g-events (LLg) are specified by the first three characteristics. High level g-events (HLg) are the result of aggregating LLg under the conditions described by the last two characteristics.*

Domains formalize g-event characteristics considering a journalistic approach. Phenomenon domain $\mathbb{D}_p$ (What) represents the universe of geographic phenomena. Spatial domain $\mathbb{D}_s$ (Where) represents a portion of geographic space that is being observed by sensors. Temporal domain $\mathbb{D}_t$ (When) represents the time for which a g-event is relevant. Recurrence domain $\mathbb{D}_r$ (How) represents the sequence of happenings of a given g-event along a time, i.e. a temporal pattern. $\mathbb{D}_a$ (Why), the causality domain, represents how g-events relate to each other in terms of geographic space and time.

B. Principles of G-event specification

Axiom 2. *Low Level g-events (LLg) are formalized by a set of properties that characterize phenomenon domain, space domain, and time domain, such that* $e :\rightarrow \{\mathbb{D}_p, \mathbb{D}_s, \mathbb{D}_t\}$.

1) Phenomenon Domain: It specifies observable phenomena in which a user is interested in. Let e be a g-event to be specified. Then $\mathbb{D}_p(e)$ describes two properties of e: a name, and a state of change observed by a sensor. A name adopts a set of keywords identifying a g-event. A state of change is detected when the observation takes one of either two value types: a transition or a threshold. Transitions describe a qualitative property, e.g. on/off, activated/deactivated, etc. Meanwhile, thresholds set a value in a numerical scale up to which a fluctuation in the observation is considered as a change.

$$\mathbb{D}_p(e) :\rightarrow \{event\_name, \\ observation : transition/threshold\}$$

2) Spatial Domain: Let e be a g-event to be specified under a geographic spatial domain. Then $\mathbb{D}_s$ describes a portion of the geographic space that is observed. In the current context $\mathbb{D}_s$ is represented by a set of sensors (s) in a network S for which $\mathbb{D}_s(e)$ is required:

$$S = \{s_1, s_2, \dots s_n\} \quad for \quad n > 0$$

s represents a tuple of the form:

$$s = \langle location : l, \quad observation : value, \\ property_1 : value, \dots \quad property_n : value\rangle$$

Then, S' represents a subset of S observing the same phenomena, and containing the same tuple structure than s.

Geographic location is given as one of the properties of s in two (x, y) or three (x, y, z) dimensional space. A function $f(l)$ transforms a set of locations in S' to any of the three primitives of geographic vector representation: point, line, and polygon. Then, it follows.

$$\mathbb{D}_s(e) :\rightarrow \{s, f(S)|s \in S)\}$$

3) Temporal Domain: For an e happening at a time t, temporal domain $\mathbb{D}_t$ describes a portion of time $T|\mathbb{D}_t(e)$ is considered relevant. Two common scenarios are assumed: a) e is relevant at any time and b) e is relevant during a specific continuous period of time constrained by a start and an end. Then, it follows:

$$\mathbb{D}_t(e) :\rightarrow \begin{cases} T = null & \text{for } e \text{ relevant anytime} \\ T = [start, end] & \text{for } e \text{ relevant at specific time} \end{cases}$$

Finally,

$$e = \{event\_name, observation, S, f(S), T\}$$

Axiom 3. *High Level g-events (HLg) represent aggregations of LLg's. Instances of a given e are aggregated based on space, time or causality. HLg are specified by describing the properties of recurrence* $\mathbb{D}_r$ *and causality* $\mathbb{D}_c$ *domains.*

4) Recurrence Domain: For a g-event e representing a LLg, recurrence domain describes a pattern in which the happening of e are aggregated into a high level g-event $(\hat{e})$. A pattern is specified by the properties:

- e, a previously specified LLg.
- o, an integer representing the number of g-event instances to be aggregated, $|o \in \mathbb{N}$
- w, a time window describing the period for which a sequence of happenings will be aggregated, $|w = [start \quad time, end \quad time]$.

$\mathbb{D}_r$ maps an existing e into $\hat{e}$ by providing values for two extra properties: o and w. Then, it follows:

$$\mathbb{D}_r(e) :\rightarrow \hat{e} = \{e, o, w\}$$

5) Causality Domain: Geographic space and time serve as contexts in which g-events are related. For instance, a car crash along a busy highway is related to a traffic jam only if they both share similar location and both happen around the same time. Causality domain $\mathbb{D}_c$ represents relations among e's, and it embeds explanatory relations among them.

Let $e_1, e_2, \dots e_n$ represent low level g-events for which a spatial and/or temporal relation needs to be represented. E represents a set containing LLgs, such as $E = \{e_1, e_2, \dots e_n\}$. Then, an $\hat{e}$ describing a desired relation can be specified by: a temporal relation within a time (T'), a spatial relation defined by $g(L)$, where L contains all the sensor locations in E; or a spatial and temporal relation combining both. It follows,

$$\mathbb{D}_c(E) :\rightarrow \hat{e} = \{E, T', L\}$$

given,

$$T' : [start \quad time, end \quad time] \\ L : geographic \quad space$$

for the cases,

$$\forall e \in E(t \in T'), \quad \text{temporal relation} \\ \forall e \in E(l \in L), \quad \text{spatial relation} \\ \forall e \in E(t \in T' \wedge l \in L), \quad \text{spatio-temporal relation}$$

Temporal relations include *before, after, within*. Spatial relations can easily be described by considering $g(L)$ as a topological function, for instance: *contains, cross, within*. The field of Geographic Information Analysis provides a large library of functions to represent temporal relations. An extra level of aggregation can be handle by combining the $\mathbb{D}_r$ and $\mathbb{D}_c$ domains (Why and How). In this way, correlations and cause-effect relations can also be represented, this issues are currently work in progress.

V. Application Cases

Three trending problems in smart cities are: vehicle allocation, air pollution, and health issues among citizens. In this section we propose solutions under an event-driven geoprocessing framework, and assess g-events as a suitable abstraction mechanism.

A. Vehicle allocation: parking assistance service

How can public space allocation be organized in the city? Parking garages around a city are to be equipped with sensors to track free and occupied parking spaces, as well as sensors to detect the arrival of a car to the gate of each parking garage. Service is assumed, for this example, to be provided from 5:00 until 23:00. Additionally, cars arriving to the parking garages are equipped with navigation systems.

An event driven Parking Management System (PMS) provides assistance for parking cars. When a car arrives at the gate of a parking garage, sensors detect its arrival; a g-event is raised and the PMS receives a notification. PMS looks into the parking records and reserves a free parking space for the arriving car.

A navigation system in the car receives a notification from the PMS indicating the location of a reserved parking space. The navigation system automatically plans a new route and directs the car to the parking space that has been reserved. If no more parking spaces are available the driver is notified, and the car is directed to the closest exit.

Alternatively, real-time information service build on top of PMS can provide drivers with information about the vacancies in each parking garage in a city, and the reservation process could start prior to the car's arrival at the parking garage. Communication among PMSs in a city allows to adjust system behavior to picks of demand for parking spaces.

Car arrival: Let e be a g-event denoting the arrival of a car to a parking garage. S represents a set of sensors at the parking garage, such that $S' \subset S$ contains the sensors at a parking gate, and $S'' \subset S$ contains the sensors monitoring parking space availability.

According to *Axiom 2*, e can be described by the properties of $\mathbb{D}_p$, $\mathbb{D}_s$, and $\mathbb{D}_t$, such as:

$$\begin{aligned}
&\mathbb{D}_p(e) :\rightarrow \{car_arrival, \quad change : True\} \\
&\mathbb{D}_s(e) :\rightarrow \{location : f(S''), \quad obs. : car_detected\} \\
&\mathbb{D}_t(e) :\rightarrow \{T : [05:00, 23:00]\}
\end{aligned}$$

Then, e is specified by the combined set of properties,

$$\begin{aligned}
e = \{&car_arrival, \quad change : True, \quad location : f(l), \\
&status : car_detected, \quad T : [05:00, 23:00]\}
\end{aligned}$$

B. Air Pollution: pollution alert service

How can an alert for high concentration of air pollutants be issued to the residents? We assume residential neighborhoods in a city are equipped with sensor networks that measure the level of pollution in the air, e.g. particular matter.

Sensor nodes are deployed around and inside neighborhoods. Awareness of the level of pollution can be used to drive citizens' behavior and reduce health risks, e.g. notify residents and recommend, for example, to avoid outdoor activities until the risk has lowered down.

An alert is raised when a pollution cloud is detected. For the current case, a pollution cloud is defined by a set of topologically connected sensor nodes which enclose an area with high pollution. No alert is raised when isolated sensor nodes reach a high level of pollution. A high level of pollution is reached when observations in a sensor node go over a predefined threshold. Constant feedback to the systems allows adjustments to the frequency of reading in the sensor network, depending of the level of risk an event represents.

High pollution: Let e be a g-event denoting a high level of pollution in a sensor node. Let $\hat{e}$ denote the detection of a pollution cloud, when a high level of pollution has been raised by at least 5 spatially related sensor nodes. Complementary, let S' denote the set of sensors measuring particulate matter (PM) levels. A high level of pollution is reached when individual observations are higher than $15.0 \quad \mu g/m_3$.

According to the *Axiom 2*, e can be described by the properties of $\mathbb{D}_p$, $\mathbb{D}_s$, and $\mathbb{D}_t$. We assume e is relevant at any time, and it exemplifies the case of spatial relation.

$$\begin{aligned}
&\mathbb{D}_p(e) :\rightarrow \{high_pollution, \quad threshold : 5.00\} \\
&\mathbb{D}_s(e) :\rightarrow S' = \{location : l, \quad obs. : Pm\} \\
&\mathbb{D}_t(e) :\rightarrow \{T : null\}
\end{aligned}$$

it follows,

$$\begin{aligned}
e = \{&high_pollution, \quad threshold : 15.00, \\
&location : l, \quad obs. : PM, \quad T : null\}
\end{aligned}$$

Pollution cloud: Axiom 3 allows to describe $\hat{e}$ as an aggregation of at least 5 e's by the properties of D_c. Then, it follows.

given,

$$\begin{aligned}
E =& \{e_1, e_2, \dots e_5\} \\
L =& \{l_1, l_2, \dots l_5\}
\end{aligned}$$

and the case for *spatial relation*,

$$\hat{e} = \{E, g(L)\}$$

C. Health Issues: reactive training service

How to promote outdoor physical activities, and enhance training services? Outdoor training services, for instance, coaching runners can be enhanced by providing awareness about the environmental conditions before and during training, and to integrate experienced users' recommendations (e.g.

sport club members) to adapt and suggest training programs. We elaborate on this application case.

A city is equipped with a network of sensors that monitor rainfall in real time. Sensor nodes are scattered in the city, placed around streets and main roads, public spaces, and recreational areas.

A mobile application provides users with a coaching service that recommends training routes based on distance, difficulty of track, scenery and other runner's preferences. It also tracks the position of the runner in real-time during training. When a runner requests a training route, a recommender system provides navigation details including: starting time, and expected ending time based on the runner's performance. The runner accepts the route and starts her training. Her mobile phone keeps track of her position along the route using the integrated navigation system. When the sensors detect rainfall in an area that intersects the runner's route, a notification is sent to the coaching service. A new route is computed in order to avoid the current and near-future rainy areas. Navigation details are sent to the runner's mobile phone in order to guide her along the new training route. If avoiding rainy areas is not possible, the runner is notified and asked if she wishes to follow the training under current constrains. Feedback from the runners community adapts the system based on new available paths and experienced runners' training-suggestions.

G-events are adopted to abstract the happenings of a training route intersecting one or more rainy areas. For the sake of simplicity, we defined rain when rainfall intensity is higher than $2mm/hour$. The relevant time of the g-event is denoted by the interval $T : [starting\ \ time,\ \ ending\ \ time]$. Ending time is updated by monitoring the speed of the runner along the route. A rainy area is defined when at least 3 sensor nodes, spatially and temporally related, report rain, S' represents a set of sensor nodes along and in the proximity of the training route.

Rain ahead: Let e be a g-event denoting 'rain' in a sensor node. Let $\hat{e}$ represent the happening of a rainy area, and $\hat{e}'$ represent the happening of a training route intersecting a rainy area. From *Axiom 2* e can be described by the properties of $\mathbb{D}_p$, $\mathbb{D}_s$ and $\mathbb{D}_t$.

$$\mathbb{D}_p(e) :\to \{rain\_fall,\ \ threshold : 2.00\}$$
$$\mathbb{D}_s(e) :\to S' = \{location : l,\ \ obs. : intensity\}$$
$$\mathbb{D}_t(e) :\to \{T : [starting\ \ time,\ \ ending\ \ time]$$

given,

$$E = \{e_1, e_2, e_3\}$$
$$L = \{l_1, l_2, l_3\}$$

then,

$$\hat{e} = \{E, g(L), T\}$$

Finally, consider $A_L = g(L)$ the location and extent of a rainy area, and R_L the location of the current training route. $g'(a, b)$ represents a spatial function that determines the relation between two geographic primitives, for instance *intersection*. Let $a = A_L$ and $b = R_L$, then $\hat{e}'$ can be represented as g-event on a second level of aggregation, as follows:

$$\hat{e}' = \{\hat{e}, g'(A_L, R_L), T\}$$

VI. Conclusion and Future Work

The utilization of spatial and temporal properties of sensor data stream can build understanding on the dynamics of the city, and provide innovative ways to improve cities' efficiency, quality of life, and productivity.

An event-driven geoprocessing framework integrates EDA and geoprocessing as a middleware component for geo-smart systems. An approach for abstracting g-events was explained and demonstrated. Specification of g-events needs to be extended to consider more complex spatial and temporal relations.

As future work, an experimental platform will deploy middleware's main components. Data streams will be simulated by deploying SOS's [11] for data collected in Santander and Eindhoven; API's on top of a SOS will allow access to data streams [12]. The approach proposed by [3] on event processing engines will allow to customize rules to access geoprocessing libraries available in PySAL and PostGIS, among others.

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