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Multi-sensory Integration for a Digital Earth Nervous System

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Abstract

The amount of geospatial data is increasing, but interoperability issues hinder integrated discovery, view and analysis. This paper suggests an illustrative and extensible solution to some of the underlying challenges, by extending a previously suggested Digital Earth Nervous System with multi-sensory integration capacities. In doing so, it proposes the combination of multiple ways of sensing our environment with a memory for storing relevant data sets and integration methods for extracting valuable information out of the rich inputs. Potential building blocks for the implementation of such an advanced nervous system are sketched and briefly analysed. The paper stimulates more detailed considerations by concluding with challenges for future research and requesting a multidisciplinary development approach – including computer sciences, environmental sciences, cognitive and neurosciences, as well as engineering.

Keywords: interoperability, sensing, observation, multi-sensory integration, digital earth.

1 Introduction and motivation

The increasing amount of geospatial data that is available from new and existing sources has inspired numerous businesses, (non-)governmental initiatives and research projects to explore ways to utilize it. The heterogeneity of data sources and diverse processing histories imply issues of syntactic and semantic interoperability. Hence, many research initiatives and projects aim to improve data interoperability. Many tackle the problem with a bottom-up approach by developing proprietary solutions for specific business problems (e.g. Xively[1], Gigwalk[2], Jana[3]), or by developing open-source solutions that allow syntactical (e.g. GDAL[4], Web 2.0 Broker[5]), or semantical (e.g. HALE[6]) translation between concrete data sources, formats and standards. Most of these have a decidedly technical perspective on standards for data formats and data exchange protocols. Others approaches address the problem top-down and aim to develop new standards that facilitate discovery, view and analysis of heterogeneous data sources. The resulting standards address interoperability on a technical level (e.g. OGC[7], ISO[8], [9]), on a semantic level (e.g. common vocabularies and code lists, e.g. DublinCore[9]), but also on a governance and legal level (INSPIRE[10], ISA[11]).

These two perspectives have resulted in substantial advances in science and operational systems. Still, all these efforts face the problem of ensuring interoperability among themselves. It is already difficult to keep track of the past and ongoing efforts, let alone to coordinate them. Although mostly adhering to common data exchange standards, the projects and initiatives originate from various academic, administrative or entrepreneurial backgrounds, and thus do not always share ideas of and approaches to interoperability. Furthermore, while opening existing data silos in formerly closed spatial data infrastructures (SDI), new silos are created as part of the process - both vertically (e.g. through incompatible organizations), and horizontally (e.g. through incompatible service buses or middleware).

The interoperability issue is aggravated by the fast-moving technological landscape: (1) new opportunities (read: platforms) emerge quickly, while others are abandoned (e.g. Gowalla[12]) or face an uncertain future (e.g. Foursquare[13]); (2) many web portals are no longer maintained after funding stopped, but many diverse government portals offers data [3]; (3) out of the numerous citizen science projects (see Sci-Starter[14] and Zooniverse[15] platforms and JRC Citizen Science and Smart Cities 2014 Summit[16]), many come with proprietary software applications; and (4) initiatives such as INSPIRE move slowly because of the legislative requirements and number of partners involved, and have difficulty adapting

[1] https://xively.com/
[2] http://gigwalk.com/
[3] http://www.jana.com/
[4] http://www.gdal.org/
[5] http://www.geotec.uji.es/web-2-0-broker-service/
[6] http://www.esdi-community.eu/projects/show/hale
[7] http://www.opengeospatial.org/
[8] http://www.isotc211.org/
[9] http://dublincore.org/
[10] http://inspire.jrc.ec.europa.eu/
[11] http://ec.europa.eu/isa/
[12] http://blog.gowalla.com/
[13] http://www.foursquare.com/
[14] http://scistarter.com/
[15] https://www.zooniverse.org/
[16] http://ies.jrc.ec.europa.eu/DE/derdu-latest-news/sdi-workshops/citizens-science-and-smart-cities-summit.html

to new technological developments, e.g. linked open data (for a discussion of differences, see Portele, C.[17]).

This paper offers an original perspective on the problem outlined above by extending and revising the conceptual model of a Digital Earth Nervous System (DENS) with the process of Multi-Sensory Integration (MSI), drawing on rich research from the cognitive and neuro-sciences, as well as sensor data fusion from engineering. The aims are threefold: (i) to stimulate and enrich the debate on interoperability for geospatial data; (ii) to increase understanding of the various interactions between geospatial data collection, transformation, processing and usage on a global scale; and (iii) to show potential future research foci. The DENS-MSI should be able to serve as a possible reference and orientation for existing approaches and projects to increase mutual understanding of interoperability challenges and how to deal with conflicting information in a decision-making environment.

The paper is not trying to create a conceptual or logical model which is complete (and overly complex) and suitable for every circumstance and situation possible. Instead it focusses on in-situ sensory and citizens' observations and aims to be simple, extensible (open world assumption), and cover the majority of cases. Neither is it meant to promote a 21st century version of the Gaia hypothesis, from which the authors would like to distance themselves.

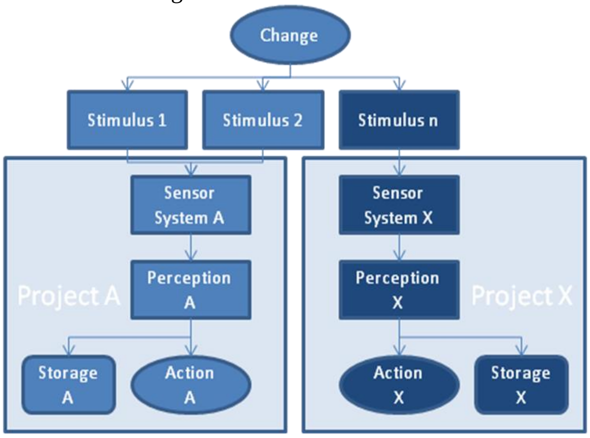
In the next section, this paper gives a short introduction to and critique of the original Digital Earth Nervous System, and its reception and usage since then. The section following it briefly explains the background of the MSI concept, which is one focus of this paper's extension of the previously suggested DENS. The last section of the paper sketches a possible integration of the DENS and MSI, and paths for future research.

2 A Digital Earth Nervous System

The DENS concept was originally formulated by DeLongueville et al. [5]. It draws an analogy to the human nervous system in order to describe and understand the processing of inputs from geospatial sensors (compare Figure 1). Here, many types of digital data and information with a geographic component can form sensory input (stimuli in Figure 1), i.e. the sensory input can range from remotely sensed spectral information of the earth's surface to geo-locatable text messages that are exchanged between citizens.

The great strength of this approach lies in its unifying vision of treating all geospatial information as potential input. It acknowledges the rise of volunteered geographic information [6, 8] and sensor networks of cheap and wireless hardware (e.g. Zigbee[18], Raspberry Pi[19]), and the need for utilizing it together with authoritative data from SDIs (see SDI cookbook chapter 10[20]), e.g. as part of quality assurance procedures. It also provides suggestions for methods to collect and store this heterogeneous geospatial information, focusing on the OGC Sensor Web Enablement (SWE) standard [2].

Figure 1: Overview of DENS.



Source: The authors.

Several studies have drawn on or from the DENS concept, e.g. a functional integration approach for the sensor web [18] and a way to sense VGI for disaster management [19]. These studies show that the DENS concept offers a valuable perspective to create original and successful ways to interact and use the various information provided. It is a reasonable assumption that developments such as cloud computing[21] and linked open data [1, 4] will improve feasibility of a DENS implementation.

However, some of the studies also showed that the DENS analogy is not suitable for all cases, or the data cannot be clearly assigned to every phase. For example, not all detailed phases of sensor processing proposed in [5] were applicable in [16]. Further, the SWE suite of standards is rather complex to implement and will not be the method of choice for many potential VGI sources – although lightweight RESTful implementations are in development [13].

The envisioned treatment of the uncertainty of VGI is another shortcoming. DeLongueville et al. [5] originally suggest that VGI needs to be validated before it is made available as an observation, but do not propose possible implementations. The current DENS approach cannot explain conflicting sensor inputs, e.g. the presence of Tweets about forest fires in an area for which remote sensing does not indicate any hot spots [20]. The human cognitive system has developed methods to deal with conflicting multi-sensory input. Contradictory sensor input can be resolved at the level of raw sensor data (stimuli and sensations) in order to check for obvious errors in sensor readings with the potential result of a re-calibration. An alternate opportunity addresses conflicts at the level of perceptions, potentially resulting in the re-evaluation of a perception.

For the latter, Spinsanti and Ostermann [20] successfully adapted an argument by Flanagin and Metzger [7] on the heuristics that humans use to deal with uncertain information: by looking into other sources ("What do others say?") and comparing the new information with existing knowledge

17 http://www.pilod.nl/index.php?title=Boek/Portele#Technical_Comparison_of_Linked_Data_and_INSPIRE

18 https://www.zigbee.org/

19 http://www.raspberrypi.org/

20 http://www.gsdidocs.org/GSDIWiki/index.php/Chapter_10

21 http://www.nist.gov/itl/cloud/

("What do I already know?"). However, the resulting method (GeoCONAVI) shows that currently it is computationally most expensive in the early stages to reduce noise, yet the most significant improvement on information quality occurs at the later stages of the processing chain, when the information had already been consolidated and clustered [16]. Multi-Sensory Integration might provide a solution for an early validation and treatment of inconsistent sensor input. We explore this option in the next section.

3 Multi-Sensory Integration

Multi-sensory integration (MSI) – also known as multi-modal integration – encompasses the process of combining the information from different sensory systems, such as visual, audio, tactile, olfactory, taste and interoception[22] by the nervous system. It is thus a crucial process without which there would be no coherent representation of the environment, and no interpretable perceptual experience. Therefore, it is also the prerequisite for any adaptive behavior and response to the environment. An important aspect of human MSI is the mutual feedback between sensory systems. Research has shown that for example visual and auditive systems influence each other, i.e. a strong signal on one "channel" can alter the perception of the other.

The nervous system integrates or segregates groups of sensory signals based on three major principles of multi-sensory integration: spatial proximity, temporal proximity, and inverse effectiveness. The first two are analogous to Tobler's First Law, while the inverse effectiveness supports an assumption that is present in the work of Spinsanti and Ostermann [20], i.e. that multiple sensor readings from different but weak sensors can together result in a valid and coherent perception. Thus, MSI results in decreased sensory uncertainty. Another desirable effect are decreased reaction times – while a system might need many stimuli from just one sensor, fewer stimuli from many sensors can lead to the same conclusion.

There are several approaches to explaining human MSI, such as visual dominance, modality appropriateness, and Bayesian integration [21]. Especially the latter might integrate well with spatio-temporal data handling. A major challenge for Bayesian integration is the assignment of probabilities of conditions to observed stimuli.

In the field of sensor engineering, the research area of sensor data or information fusion has already seen a lot of activity [14]. The majority of research until now has focused on low-level abstracted sensor data, i.e. low-dimensional, continuous data from sensors with a known uncertainty, on data fusion from several but similar sensors, or on different but related sensors in close spatial proximity (e.g. robotics). The integration of heterogeneous sensors covering irregular areas, e.g. wireless sensor networks from citizens or geosocial network data (hard/soft data integration from disparate sensors in the terminology of [14]) has seen less activity.

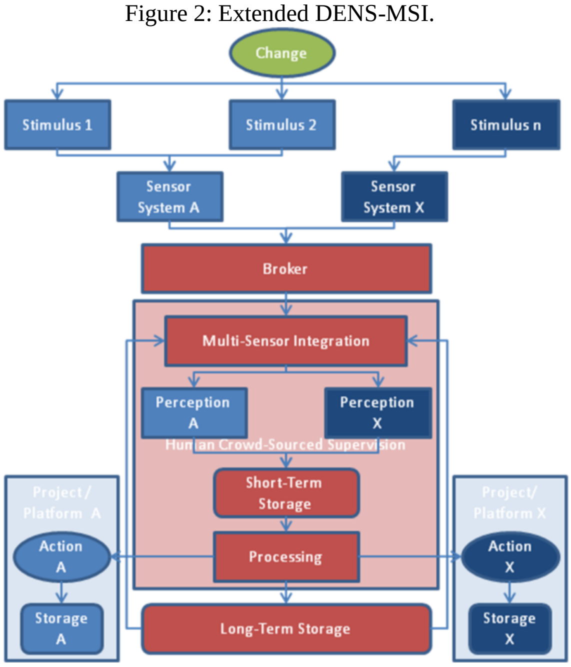
The following section will investigate how these concepts from cognitive science and information fusion could be fruitful motivations for future research in the areas of (geo)sensor web and (geo)social networks.

4 Design and implementation of a DENS

In this section, we show how concepts and theories from neuroscience and robotics can contribute to an overall understanding and improvement of geospatial data interoperability on a global scale. We directly build on previous work on DENS, which only addressed observations from a single source and sequences of data flows.

The following Figure 2 shows an extended and revised DENS-MSI and contains all the elements and processes we will discuss. As we will argue, this raises three main challenges: first, the choice of senses (sensors) and their interoperability; second, the choice of memory (geospatial data sets); and third, the choice of actual MSI methods.

Figure 2: Extended DENS-MSI.



Source: The authors

It all begins with an observable change in the environment, for example, in the case of a forest fire remote sensing, satellites can detect higher temperatures on the ground, smoke plumes, and citizens and practitioners on the ground begin to discuss and share information. This creates stimuli which are observed by sensor systems, e.g. Twitter, OSM, Flickr or satellites.

Considering the many potential sensors that the DENS can "listen" to, we need to identify those with the highest likelihood of containing information about the phenomenon that we are interested in (the right cues for combination). Thus, we need to have prior knowledge about the phenomenon and codify it in rules. For example, the utility of some sensor systems depend on the time of the day (just as human sensor systems do), e.g. whether it is day or night. As a first step, a brokering [15] approach[23] can help to integrate the sensor data on the technical and syntactic interoperability level. The next level would be semantic integration or

[22] sensitivity to stimuli originating inside of the body;

[23] http://www.essi-lab.eu/do/view/GIaxe/WebHome

interoperability through ontologies, metadata, and vocabularies [17].

Yet, it remains questionable whether it is feasible to semantically enrich sensor data on a low (atomic) level [10], because of the number of potential sensors readings that need processing and the exponential growth of links that might not in fact be sensible. It seems more appropriate to do the linking and semantic enrichment on the higher level of perceptions. On the level of individual stimuli, it seems more reasonable to check (i) whether the source is trusted (or neutral); and (ii) which (if any) detectable keywords are included, instead of analyzing the content and context in detail. The resulting sensor set can then be used for the actual MSI.

The three major principles from neuroscience and cognitive science (spatial and temporal proximity, inverse effectiveness) show a clear alignment with the core principles of processing spatio-temporal data: what is near in space and time is related. This strengthens the analogy between human and digital earth nervous system. If multiple sensory inputs are available, then a DENS-MSI can rely on cue combination, i.e. a comparison of the various sensor inputs. In the optimal case, these can be unified in single coherent perception (e.g. remote sensing shows smoke plume over forests, Tweets talk about fire). However, if the cues are dissonant (e.g. Tweets show talk about forest fire in location X, but a visual live stream from a web cam showing nothing extraordinary or no smoke), causal inference provides an alternative. Causal inference is a crucial component in human perception and uses prior knowledge to resolve the conflicting sensor inputs by resorting to causal structures. It determines the most plausible causal structure to explain the dissonance. In the example above, possible causal structures are a sensor misreading (interpretation of Tweets), or temporal misalignment (remote sensing images do not match the exact same period). Here we tap into cognitive processes, especially long-term memory retrieval, in order to determine the most likely causal structure. For the MSI, the system would have to be able to assign likelihoods based on prior knowledge codified as machine-readable information. This is analogous to the GeoCONAVI use of authoritative datasets [16]. Given the large number of data sets available, we need to identify those that are the most relevant for the task or phenomenon. This corresponds to geographic information retrieval, with the important question: which data sets (i.e. knowledge) to choose? Ivanova [12] explores a solution based on domain expert input.

The research from sensor data fusion has only recently begun to investigate the particular issues found with integration disparate sensors and hard/soft data, i.e. geospatial sensor networks from humans, low-cost in-situ sensors, and remote sensing. However, in addition to the Bayesian probabilistics discussed above, possibilistic and human centered approaches are investigated. While the former offers potential solutions that need further exploration, the latter one relates to crowd-sourcing tasks (see below).

Continuing our thought experiment, the integrated sensory information results in perceptions of events on the Earth, e.g. forest fires. We can expect many such perceptions. These and the corresponding stimuli are stored in a short-term memory for immediate reference. This short-term memory is constantly analyzed (searched for patterns) and monitored. Only when a number of criteria (rules) are fulfilled is an alert being raised (e.g. several perceptions relating to forest fires in close spatial and temporal proximity). Similarly to the MSI, this filtering can be supervised by crowd-sourcing efforts.

As a last step, verified sensor information can be stored in a long-term memory to be accessed for future multi-sensory integration, or other geographic information retrieval tasks. The short-term memory and long-term memory together form a 'Digital Earth Memory System'.

Clearly, a challenge is to train such a semi-autonomous system to filter and sort stimuli, query existing data sets for validation, integrate heterogeneous sensor data and monitor perceptions that are stored. Supervised machine learning would need constant human supervision, but this is actually a process that can be very well crowd-sourced. A constant stream of a stratified sample of the DENS perceptions could be used for this purpose. The stimuli that are part of these perceptions are checked by volunteers and micro-tasked paid crowd-workers. Hung [11] shows the feasibility of methods to filter out spammers and low-quality contributions. For example, they could check whether a Tweet that supposedly belongs to a perception "forest fire near Avignon, France" is actually about a forest fire in France). Gamification offers even more opportunities, e.g.[15].

5 Conclusions and outlook

This paper aimed to stimulate the debate on interoperability for geospatial observations, to increase understanding of the various interactions between geospatial data collection, transformation, processing and usage on a global scale, and to show potential future research foci.

Indeed, the paper has highlighted developments in and important challenges for improving interoperability of heterogeneous geospatial data sources. We have argued that the concept of the DENS can help and improve mutual understanding between practitioners, researchers, developers and citizens. Further, the paper has shown how knowledge from the disciplines of cognitive and neurosciences, as well as engineering can contribute to an improved DENS model.

Particularly promising research objectives include the assessment of a sensor's observations' validity through possibilistic methods and the use of crowd-sourcing to supervise machine learning of algorithms and rules to filter, sort and organized stimuli into coherent perceptions.

Arguably, too specific approaches had little success in increasing interoperability until now, while there is some risk of failure for over-generic approaches. Therefore, we suggest following a stepwise and incremental development methodology. We plan to use well examined cases, such as the forest fire [16, 18, 20] or flood [19] examples for the initial set-up of a possible solution, before moving into new areas. Here, we will address urban environments, which should provide a solid ground for, especially because of the related high traffic in social media.

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