Earth observation big data analytics in operating mode for GIScience applications. The (GE)OBIA acronym(s) reconsidered

Andrea Baraldi, Stefan Lang, Dirk Tiede, Thomas Blaschke

▶ To cite this version:

Andrea Baraldi, Stefan Lang, Dirk Tiede, Thomas Blaschke. Earth observation big data analytics in operating mode for GIScience applications. The (GE)OBIA acronym(s) reconsidered. GEOBIA 2018 - From pixels to ecosystems and global sustainability , Centre d'Etudes Spatiales de la BIOsphère (CESBIO); Office national d'études et de recherches aérospatiales (ONERA); Espace pour le développement (ESPACE DEV); UMR TETIS, Jun 2018, Montpellier, France. hal-01958406

HAL Id: hal-01958406

https://hal.univ-reunion.fr/hal-01958406

Submitted on 12 Apr 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Earth observation big data analytics in operating mode for GIScience applications – The (GE)OBIA acronym(s) reconsidered

Andrea Baraldi[1,2,*], Stefan Lang[1], Dirk Tiede[1], and Thomas Blaschke[1]

1. Department of Geoinformatics – Z_GIS, University of Salzburg
Schillerstr. 30, 5020 Salzburg, Austria
2. Italian Space Agency (ASI), Via del Politecnico, 00133 Roma RM, Italy
** Correspondence: andrea6311@gmail.com*

ABSTRACT. *Pre-dated by spatial context-sensitive image classification algorithms, developed by the remote sensing (RS) and computer vision (CV) communities as viable alternatives to traditional pixel-based image analysis since the late '70s, in year 2006 the geographic information science (GIScience) community introduced terms "object-based image analysis" (OBIA) and geographic OBIA (GEOBIA) to "bridge the gap between geographic information systems (GIS) and RS". Following year 2000, two driving forces working in closed-loop fostered the emergence of a GEOBIA subfield within the GIScience community. On the one hand, a portion of the GIScience community adopted de-facto the eCognition commercial image processing software toolbox, brought to market in year 2000, as a CV system reference standard. On the other hand, the GIScience community lacked communication with the multi-disciplinary realm of cognitive science, encompassing philosophy, psychophysics, neouroscience, machine learning-from-data, artificial general intelligence (AGI), which includes CV as superset of Earth observation (EO) image understanding, and GIScience. One fundamental proof of the self-referential syndrome affecting the GEOBIA community is that, to date, the mainstream RS and CV solutions ignore standard GEOBIA algorithms and vice versa. Unequivocal true-facts about biological vision and primate visual perception recommend reconsidering the relevance of acronyms OBIA/GEOBIA. Acknowledged that "science progresses one funeral at a time", to successfully cope with EO big data analytics characterized by the five Vs of volume, velocity, variety, veracity and value, the GEOBIA community is wished to gather sufficient intellectual fortitude to change its own name into a more exact one, such as EO for GIScience (EO4GEO), meaning EO big data analytics in operating mode for GIScience applications, constrained by 2D (retinotopic, spatial topology-preserving) image analysis in cognitive science (2D-EO4GEO).*

KEYWORDS: *hybrid (combined deductive and inductive) inference, object-based image analysis (OBIA), physical and statistical data models, radiometric calibration, spatial topological and spatial non-topological information components, vision, world model.*

1. Introduction

Synonym of scene-from-image reconstruction and understanding, vision is an inherently ill-posed cognitive (*information-as-data-interpretation*) problem (Capurro and Hjørland, 2003), see Figure 1. Encompassing both biological vision and computer vision (CV), vision is inherently ill-posed because affected by: (I) a data dimensionality reduction, from the 4D space-time scene-domain to the (2D) image-domain, and (II) a semantic information gap from ever-varying sensory data (sensations) in the image-domain to stable percepts in the mental model of the world-scene (conceptual world model) (Matsuyama and Hwang, 1990). Hence, vision is very difficult to solve. It is non-polynomial hard (NP-hard) in computational complexity (Frintrop, 2011; Tsotsos, 1990) and requires *a priori* knowledge in addition to sensory data to become better conditioned for numerical solution (Cherkassky and Mulier, 1998).

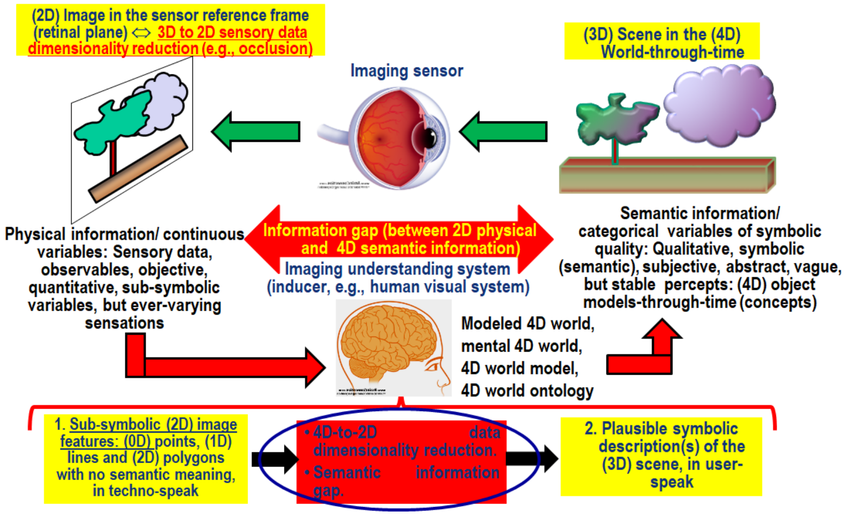


FIGURE 1. *Vision is synonym of scene-from-image reconstruction and understanding. This is an inherently ill-posed cognitive problem, non-polynomial (NP)-hard in computational complexity and requiring a priori knowledge in addition to sensory data to become better conditioned for numerical solution. Vision is inherently ill-posed in the Hadamard sense because it is affected by: (i) a 4D-to-2D data dimensionality reduction problem from the spatiotemporal 4D world-domain to the (2D) image-domain, e.g., responsible of visual occlusion phenomena; (ii) a semantic information gap, from ever-varying sensory data (sensations) in the (2D) image-domain to stable concepts (percepts) in the 4D scene-domain.*

In a Bayesian approach to vision, Bayesian priors, also known as Marr's constraints (Marr, 1982; Quinlan, 2012), have been incorporated into the human visual system over the course of its evolutionary history (Poggio, 2012). For example, in biological vision, panchromatic and chromatic image understandings are nearly as effective. It means that spatial information typically dominates color information in vision (Matsuyama and Hwang, 1990). Hence, one possible constraint eligible for use by inherently ill-posed CV systems to become better conditioned for numerical solution is to perform nearly as well when input with panchromatic and chromatic imagery, whose necessary not sufficient pre-condition is exploitation of primary spatial information in addition to secondary color information. Noteworthy, color information is the sole visual information component available at sensor (pixel) resolution. The undisputable true-fact that, in vision, spatial information dominates color information is foundational for the "object-based image analysis" (OBIA) and geographic OBIA (GEOBIA) paradigm (Benz *et al.*, 2004; Blaschke and Lang, 2006; Blaschke *et al.*, 2014; Hay and Castilla, 2008; Lang and Blaschke, 2006), proposed as a spatial context-sensitive CV solution alternative to traditional spatial context-insensitive (pixel-based) 1D image analysis, where spatial topological and/or spatial non-topological information components are totally ignored, see Figure 2.

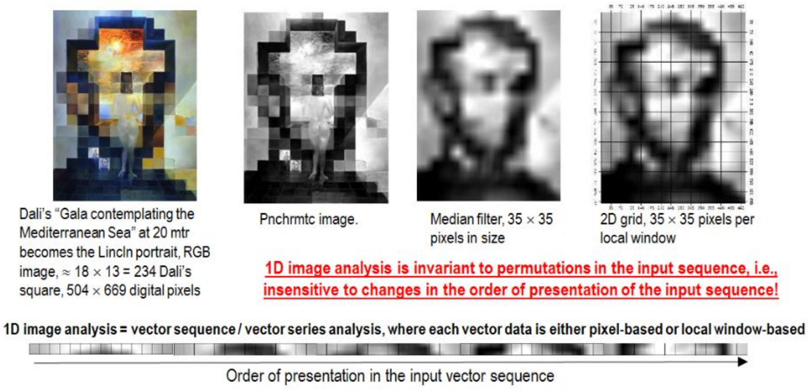


FIGURE 2. *Example of 1D image analysis, either spatial context-insensitive (pixel-based) or spatial context-sensitive (e.g., local window-based). Synonym of 1D analysis of a 2D gridded dataset, it is affected by spatial data dimensionality reduction. The (2D) image at left is transformed into the 1D vector data stream shown at bottom, where vector data are either pixel-based or spatial context-sensitive, e.g., local window-based. This 1D vector data stream, either pixel-based or local window-based, means nothing to a human photointerpreter. When it is input to a traditional inductive data learning classifier, such as a Support Vector Machine (SVM) or Random Forest (RF), this 1D vector data stream is what the inductive classifier actually sees when watching the (2D) image at left. Undoubtedly, computers are more successful than humans in 1D image analysis, invariant to permutations in the input vector data sequence, such as in orderless pooling encoders (Cimpoi et al., 2014). Nonetheless, humans are still far more successful than computers in 2D image analysis, synonym of spatial topology-preserving*

(retinotopic) image analysis (Tsotsos, 1990), sensitive to permutations in the input vector data sequence, such as in order-sensitive pooling encoders (Cimpoi et al., 2014).

As an instance of cognitive tasks, vision is investigated by the multi-disciplinary realm of cognitive science, encompassing philosophy, psychophysics, neouroscience, machine learning-from-data, artificial general intelligence (AGI), which includes CV as superset of Earth observation (EO) image pre-processing and understanding (IU), i.e., CV $\supset$ EO-IU, and geographic information science (GIScience), see Figure 3.

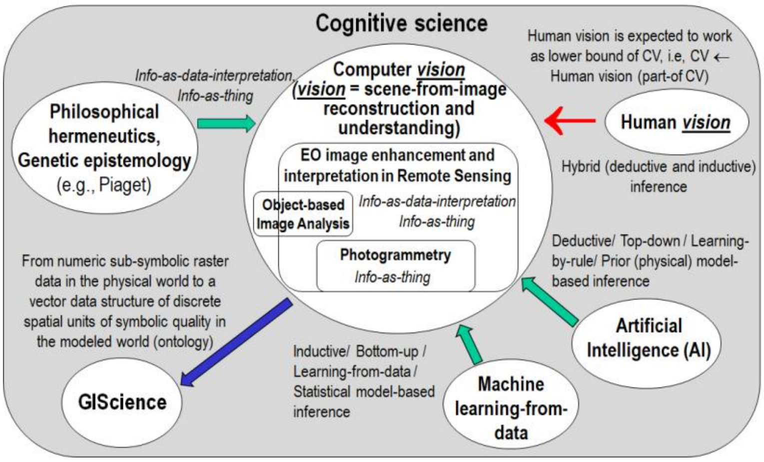


FIGURE 3. *Cognitive science is the interdisciplinary scientific study of the mind and its processes. It examines what cognition (learning) is, what it does and how it works. It especially focuses on how information/knowledge is represented, acquired, processed and transferred within nervous systems (distributed processing systems in humans, such as the human brain, or other animals) and machines (e.g., computers). Neurophysiology studies nervous systems, including the brain. Human vision is expected to work as lower bound of computer vision (CV), i.e., 'human vision $\rightarrow$ (part-of) CV', such that inherently ill-posed CV is required to comply with human visual perception phenomena to become better conditioned for numerical solution.*

The development of artificial satellites in the latter half of the 20th century allowed remote sensing (RS) in general, and EO-IU in particular, to progress to a global scale by the end of the Cold War. Ever since, EO-IU $\subset$ CV applications have been a typical example of *big data* analytics, well before term "big data", associated with the five Vs of volume, velocity, variety, veracity and value (Yang *et al.*, 2017), became increasingly popular with the diffusion of the world wide web, starting from the '90s. In recent decades, spaceborne/airborne EO imagery has been increasingly adopted as a relevant sensory data source in GIScience applications at large spatial extents, from regional to world scale, due to high-frequency data acquisition, coarseto-fine spatial resolution, low costs for data purchase or free-of-cost data policies, and ever-decreasing costs in storage and processing.

Pre-dated by spatial context-sensitive image classification algorithms developed by the RS and CV communities as viable alternatives to traditional pixel-based image analysis since the late ‘70s (Haralick and Shapiro, 1985; Horowitz and Pavlidis, 1974, Ketting and Landgrebe, 1976; Matsuyama and Hwang, 1990; Nagao and Matsuyama, 1980; Ohlander *et al.*, 1978), in year 2006 the GIScience community introduced terms “object-based image analysis” (OBIA) and geographic OBIA (GEOBIA) to “bridge the gap between geographic information systems (GIS) and RS” (Benz *et al.*, 2004; Blaschke and Lang, 2006; Blaschke *et al.*, 2014; Hay and Castilla, 2008; Lang and Blaschke, 2006). Following year 2000, two driving forces working in closed-loop fostered the emergence of a GEOBIA subfield within the GIScience community. On the one hand, a portion of the GIScience community adopted *de-facto* the eCognition commercial image processing software toolbox, brought to market in year 2000, as a CV system reference standard (Trimble, 2015). On the other hand, the GIScience community lacked communication with the RS and CV communities within the multi-disciplinary realm of cognitive science, see Figure 3.

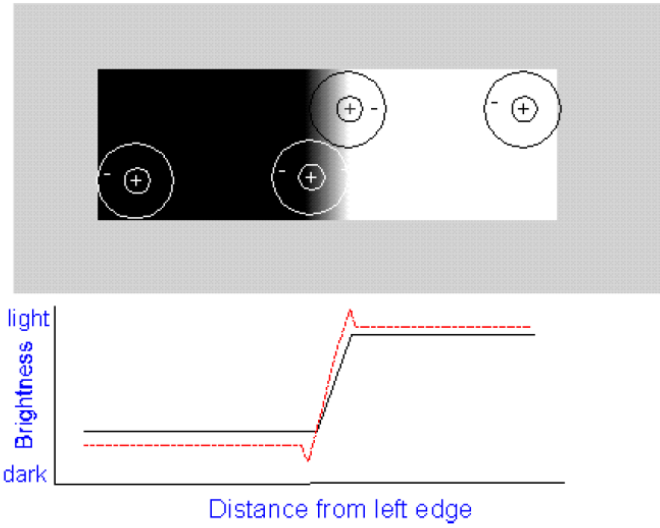


FIGURE 4. *Mach bands illusion. In black: Ramp in luminance units across space. In red: Brightness (perceived luminance) across space. One of the best-known brightness illusions is the psychophysical phenomenon of the Mach bands: where a luminance (radiance, intensity) ramp meets a plateau, there are spikes of brightness, although there is no discontinuity in the luminance profile. Hence, human vision detects two boundaries, one at the beginning and one at the end of the ramp in luminance. Since there is no discontinuity in luminance where brightness is spiking, the Mach bands effect is called a visual “illusion”. Along a ramp, no image-contour is perceived by human vision, irrespective of the ramp’s local contrast (gradient) in*

range (0, $+\infty$). In the words of Pessoa, "if we require that a brightness model should at least be able to predict Mach bands, the bright and dark bands which are seen at ramp edges, the number of published models is surprisingly small" (Pessoa, 1996). The important lesson to be learned from the Mach bands illusion is that local variance, contrast and first-order derivative (gradient) are statistical features (data-derived numeric variables) computed locally in the (2D) image-domain NOT suitable to detect image-objects (segments, closed contours) required to be perceptually "uniform" ("homogeneous") in agreement with human vision. In other words, these popular local statistics are not suitable visual features if detected image-segments/image-contours are required to be consistent with human visual perception, including ramp-edge detection. This straightforward (obvious), but not trivial observation is at odd with a large portion of existing CV, RS and GEOBIA literature, where many semi-automatic image segmentation (Baatz et al., 2000) and/or image-contour detection algorithms (Canny, 1986; Smith and Brady, 1997) are based on heuristic thresholding a local variance, contrast or gradient.

One fundamental proof of the self-referential syndrome affecting the GEOBIA community is that, to date, the mainstream RS and CV solutions ignore standard GEOBIA algorithms and vice versa. For example, the eCognition first stage consists of an inductive inherently ill-posed multi-resolution image region-growing algorithm (Baatz and Schäpe, 2000), which requires several system's free-parameters to be user-defined based on heuristics to become better conditioned for numerical solution. The region-growing principle adopted by the eCognition multi-scale image segmentation algorithm is a heuristic-based multiple thresholding criterion of a local variance estimate. Local variance, local contrast and local first-order derivative are well-known visual features widely adopted in the RS and CV literature to cope with the dual problems of image-contour detection (Canny, 1986; Smith and Brady, 1997) and image segmentation (Haralick and Shapiro, 1985; Horowitz and Pavlidis, 1974, Ketting and Landgrebe, 1976; Matsuyama and Hwang, 1990; Nagao and Matsuyama, 1980; Ohlander *et al.*, 1978). To make it appealing to a GIScience community, familiar with the concept of spatial scale in geographic maps, eCognition misleadingly identifies a local variance threshold parameter, widely adopted in traditional CV and RS algorithms, with a "(spatial) scale parameter" (Trimble, 2015). Intuitively, when a local variance threshold is relaxed, image-regions grow larger, like if they were detected at coarser spatial scale. The conceptual fact that the eCognition so-called scale parameter is actually a heuristic-based local variance threshold has negative practical consequences. In common practice, the eCognition inductive image segmentation first stage is inherently semi-automatic, site-specific and inconsistent with human visual perception phenomena (Baraldi, 2017; Marr, 1982; Yellott, 1993), such as the well-known Mach bands visual illusion affecting ramp-edge detection (Pessoa, 1996), see Figure 4. Hence, it tends to score "low" in operating mode, when coping with EO big data characterized by the five Vs of volume, variety, veracity, velocity and value (Yang *et al.*, 2017). Adopted as an image segmentation reference standard by the GEOBIA community, the eCognition heuristic-based image region-growing first stage is almost ignored to date by the RS and CV communities when involved with low-level image segmentation tasks.

In the rest of this work, a CV $\supset$ EO-IU system (see Figure 3) is defined in operating mode if and only if it scores "high" in all indexes belonging to a minimally dependent and maximally informative (mDMI) set of EO outcome and process (OP) quantitative quality indicators (Q^2Is), to be community-agreed upon to be used by members of the community, in agreement with the intergovernmental Group on Earth Observations (GEO)-Committee on Earth Observation Satellites (CEOS) Quality Accuracy Framework for Earth Observation (QA4EO) calibration/validation (*Cal/Val*) guidelines (GEO-CEOS, 2010). A proposed instantiation of an mDMI set of EO OP-Q^2Is includes (Baraldi, 2017): (i) degree of automation, inversely related to human-machine interaction, (ii) effectiveness, e.g., thematic mapping accuracy, (iii) efficiency in computation time and in run-time memory occupation, (iv) robustness (vice versa, sensitivity) to changes in input data, (v) robustness to changes in input parameters to be user-defined, (vi) scalability to changes in user requirements and in sensor specifications, (vii) timeliness from data acquisition to information product generation, (viii) costs in manpower and computer power, (ix) value, e.g., semantic value of output products, economic value of output services, etc.

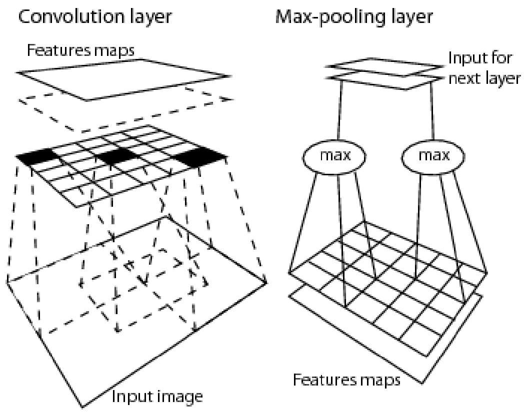


FIGURE 5. *2D image analysis, synonym of spatial topology-preserving (retinotopic) feature mapping in a (2D) image-domain (Tsotsos, 1990). Activation domains of physically adjacent processing units in the 2D array of convolutional spatial filters are spatially adjacent regions in the 2D visual field. Provided with a superior degree of biological plausibility in modelling 2D spatial topological and spatial non-topological information, distributed processing systems capable of 2D image analysis, such as deep convolutional neural networks (DCNNs), typically outperform traditional 1D image analysis approaches. Will computers become as good as humans in 2D image analysis?*

A reverse case proving the relative isolation of the GEOBIA community is the recent hype on deep convolutional neural networks (DCNNs), which has been spreading from the CV to the RS community, without affecting the GEOBIA subfield, yet. Provided with a superior degree of biological plausibility in modelling 2D spatial topological and spatial non-topological information (Tsotsos, 1990), distributed processing systems capable of 2D image analysis, such as DCNNs and order-sensitive pooling encoders (Cimpoi *et al.*, 2014), see Figure 5, are sensitive to changes in the order of presentation of the input sequence, i.e., they are sensitive to permutations in the input data set. 2D image analysis algorithms typically outperform traditional 1D image analysis approaches, either spatial context-dependent (e.g., window-based, image-object-based) or spatial context-independent (pixel-based), insensitive to permutations in the 1D input vector data sequence, see Figure 2. Typical examples of 1D image analysis approaches are orderless pooling encoders (Cimpoi *et al.*, 2014) together with a great portion of GEOBIA solutions where an image segmentation first stage, followed by a per-segment shape and color feature extraction, is input as 1D vector data sequence to a vector data classifier, such as a plug-in maximum likelihood (ML) classifier or an inductive learning-from-data multi-layer perceptron (MLP), support vector machine (SVM) or random forest (RF) (Cherkassky and Mulier, 1998), where spatial topological information is ignored, see Figure 2.

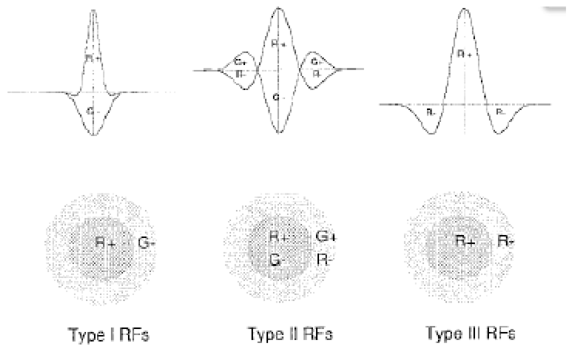
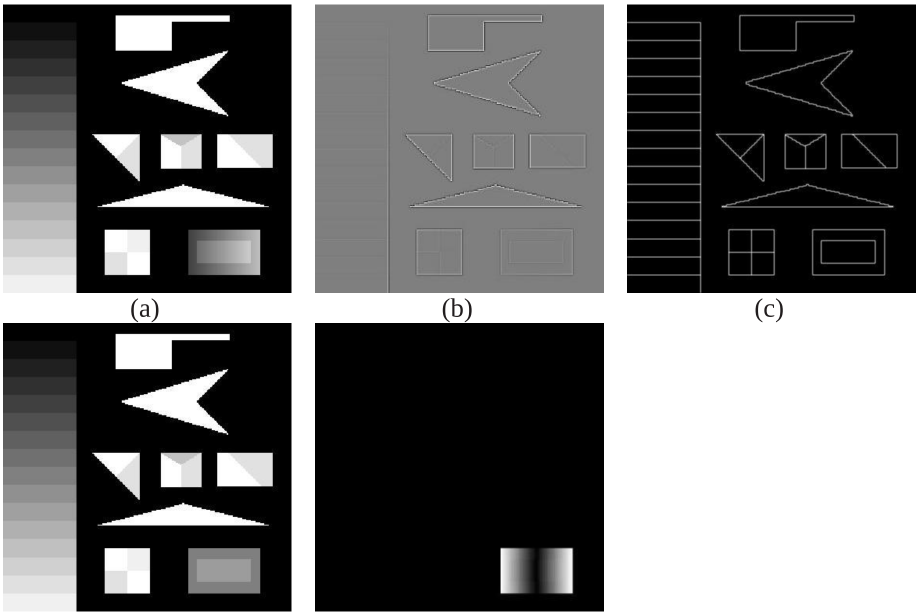


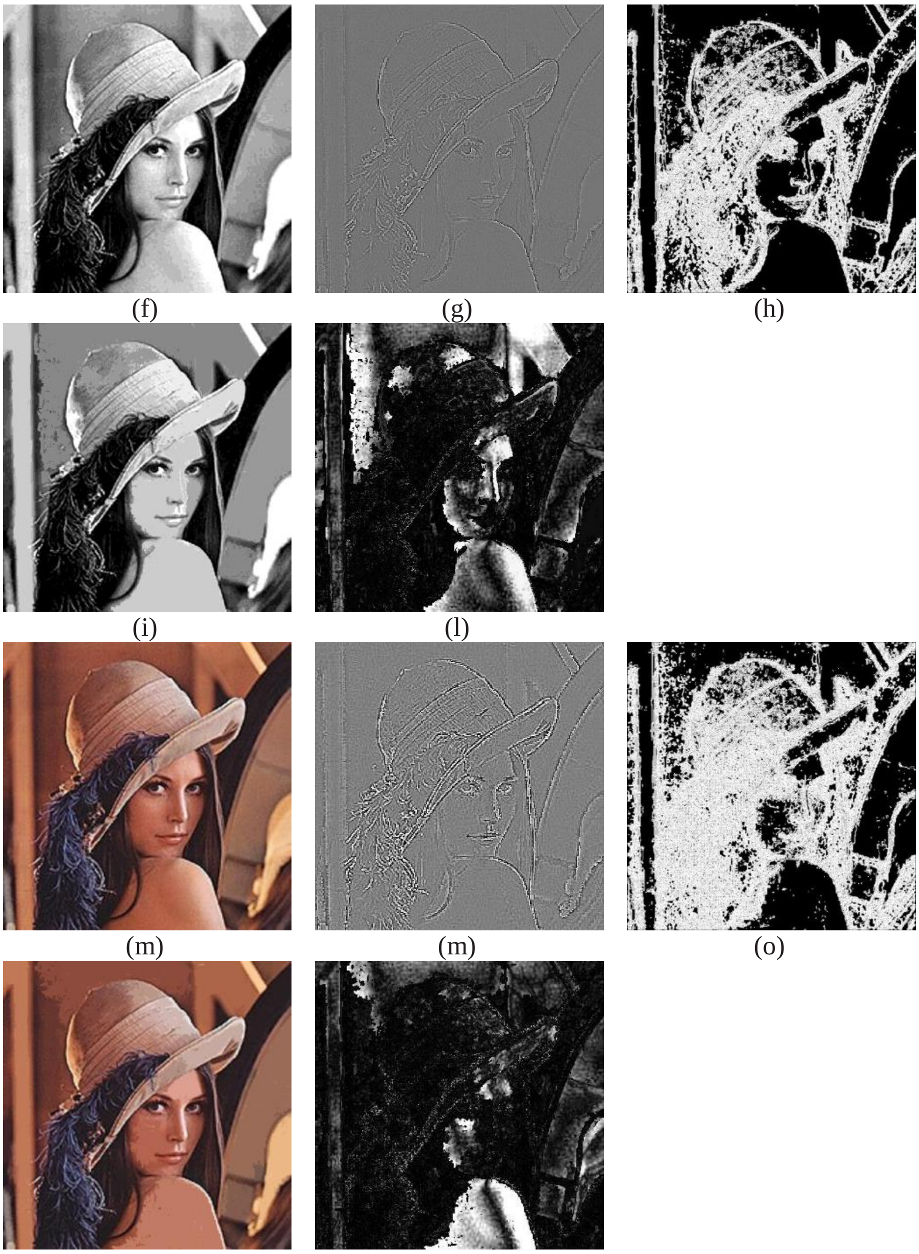
FIGURE 6. *Approximating receptive fields (RF) of single-opponent cells (Type I), double-opponent cells (Type II) and achromatic Type III visual cells with Gabor wavelet filters (Jain and Healey, 1986; Marr, 1982; Baraldi, 2017). These trimodal 2D wavelet-based spatial filters are necessary and sufficient to accomplish: (i) automated panchromatic and chromatic image-contour detection as zero-crossings (spatial changes in sign) of a second-order derivative of a local Gaussian function (low-pass filter), equivalent to a local concavity estimator, (ii) well-posed (deterministic) image segmentation (superpixel detection, texel detection) from image-contours, see Figure 7, and (iii) texture segmentation from texels based on third-order spatial autocorrelation statistics (Baraldi, 2017; Yellott, 1993), in agreement with the Marr's raw and full primal sketch in low-level vision (Marr, 1982).*

In addition to failing to communicate with each other, the GEOBIA, RS and CV communities typically share little or no knowledge about cognitive science in general, see Figure 3, encompassing biological vision (Hubel and Wiesel, 1959; Kandel and Schwartz, 1991; Jain and Healey, 1998; DiCarlo, 2017), see Figure 6 and Figure 7, and primate visual perception (Baraldi, 2017; Marr, 1982; Pessoa, 1990; Vecera and Farah, 1997), see Figure 4. As a consequence, inherently ill-posed CV systems typically rely on heuristics rather than complying with human visual perception phenomena to become better conditioned for numerical solution, so that 'human vision $\rightarrow$ (part-of) CV', see Figure 3. In the words of Iqbal and Aggarwal: "frequently, no claim is made about the pertinence or adequacy of the digital models as embodied by computer algorithms to the proper model of human visual perception... This enigmatic situation arises because research and development in computer vision is often considered quite separate from research into the functioning of human vision. A fact that is generally ignored is that biological vision is currently the only measure of the incompleteness of the current stage of computer vision, and illustrates that the problem is still open to solution" (Iqbal and Aggarwal, 2001).



(a) (b) (c)

(d) (e)

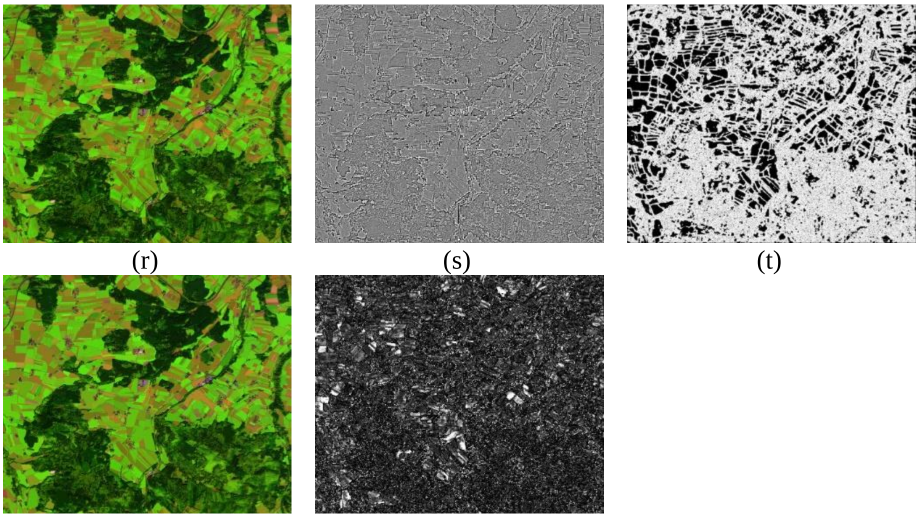


(f) (g) (h)

(i) (l)

(m) (m) (o)

(p) (q)



(r) (s) (t)

(u) (v)

FIGURE 7. *To comply with constraint 'human vision → CV ⊃ EO-IU in operating mode' (see Figure 3), the automated EO-IU subsystem proposed in Baraldi (2017), requiring no human-machine interaction to run, is tested on complex EO spaceborne/airborne panchromatic and chromatic images if and only if it performs in agreement with human visual perception, starting from the Mach bands illusion, see Figure 4, on simpler test cases of increasing signal complexity. (a) SUSAN synthetic panchromatic image (Smith and Brady, 1997), byte coded in range {0, 255}. Step edges and ramp edges at known locations (the latter forming the two inner rectangles visible at the bottom right corner) form angles from acute to obtuse. According to human vision, 31 image-segments can be detected as reference "ground-truth". (b) Sum (synthesis) of the wavelet-based near-orthogonal multi-scale multi-orientation image decomposition. Filter value sum in range [-255, +255]. (c) Automated (requiring no human-machine interaction) image segmentation into zero-crossing (ZX) segments generated from ZX pixels detected by a multi-scale multi-orientation filter bank, different from Marr's single-scale isotropic ZX pixel detection (Marr, 1982). Exactly 31 image-segments are detected with 100% contour accuracy. Segment contours depicted with 8-adjacency cross-aura values in range {0, 8} (Baraldi, 2017). (d) Image-object mean view (Trimble, 2015) = object-wise constant input image reconstruction. (e) Object-wise constant input image reconstruction compared with the input image, per-pixel root mean square error (RMSE) in range [0, 255]. (f) Natural panchromatic image of Lenna. (g) Same as (b). (h) Same as (c), there is no CV system's free- parameter to be user-defined. (i) Same as (d). (l) Same as (e). (m) Natural RGB-color image of Lenna. (n) Same as (b). (o) Same as (c), there is no CV system's free- parameter to be user-defined. (p) Same as (d). (q) Same as (e). (r) Zoom-in of a Sentinel-2A MSI Level-1C image of the Earth surface south of the city of Salzburg, Austria. Acquired on 2015-09-11. Spatial resolution: 10 m. Radiometrically calibrated into top-of-atmosphere reflectance (TOARF) values in range {0, 255}, it is depicted as a false color RGB*

image, where: R = Medium InfraRed (MIR) = Band 11, G = Near IR (NIR) = Band 8, B = Blue = Band 2. Standard ENVI histogram stretching applied for visualization purposes. (s) Same as (b). (t) Same as (c), there is no CV system's free- parameter to be user-defined. (u) Same as (d). (v) Same as (e).

In line with the quote from Iqbal and Aggarwal and with Figure 3, Marcus states "there is no need for machines to literally replicate the human mind… But there remain many areas, from natural language understanding to commonsense reasoning, in which humans still retain a clear advantage; learning the mechanisms underlying those human strengths could lead to advances in AI, even if its goal is not, and should not be, an exact replica of human brain. For many people, learning from humans means neuroscience... We don't yet know enough about neuroscience to literally reverse engineer the brain... in the meantime, it should certainly be possible to use techniques and insights drawn from cognitive science and developmental psychology, now, in order to build more robust and comprehensive AI, building models that are motivated not just by mathematics, but also by clues from the strengths of human psychology." (Marcus, 2018).

The rest of this paper is organized as follows. Stemming from preliminary concepts, definitions and observations discussed in the present Chapter 1, a critical appraisal of acronyms OBIA and GEOBIA is proposed in Chapter 2. In Chapter 3, acknowledged that "science progresses one funeral at a time" (Axios, 2017), which reduces the risk of getting trapped in a local minimum of a solution space, the GEOBIA community is recommended to reconsider the relevance of acronyms OBIA/GEOBIA when coping with the five Vs of volume, velocity, variety, veracity and value characterizing EO big data analytics, It means the GEOBIA community is encouraged to find the intellectual fortitude to change its name into a more exact one.

2. Critical appraisal of acronyms OBIA and GEOBIA

Alternative to traditional pixel-based image analysis where spatial topological and spatial non-topological information components are totally ignored, the OBIA/GEOBIA paradigm (Benz *et al.*, 2004; Blaschke and Lang, 2006; Blaschke *et al.*, 2014; Hay and Castilla, 2008; Lang and Blaschke, 2006) is founded upon the unquestionable true-fact that spatial information dominates color information in vision (Matsuyama and Hwang, 1990). Stemming from preliminary concepts, definitions and observations proposed in Chapter 1, a first consideration is that acronym OBIA is equivocal because word 'object' in vision may refer to either a sub-symbolic planar object in the image-domain or a real-world symbolic object in the 4D spatio-temporal scene-domain, see Figure 1. To avoid this ambiguity, acronym OBIA should be reformulated as image-object-based image analysis, synonym of "segment-based image-analysis" predated in the RS and CV literature since the late '70s. Unfortunately, image-object-based image analysis is a tautology. In primates, low-level image segmentation is pre-attentive, fast and parallel (Kandel and Schwartz, 1991; Baraldi, 2017; DiCarlo, 2017). It is also known as raw primal sketch for token detection (Marr, 1982), where tokens include: (a) closed-contours as texture elements (texels), to be input to a full primal sketch detector for texture segmentation, and (b) keypoints (end-points, corners, T-junctions and X-junctions) eligible for saliency map detection as input to an attentional high-level vision second stage (Frintrop, 2011; Kandel and Schwartz, 1991; Baraldi, 2017). In the Marr terminology, pre-attentional (low-level) image segmentation is followed by a pre-attentional full primal sketch (Marr, 1982), known as texture segmentation (Yellott, 1993; Baraldi, 2017). In primate low-level vision, image segmentation is a hybrid (combined deductive/top-down and inductive/bottom-up) inference process (Vecera and Farah, 1997). In other words, there is no vision without image segmentation for token detection and texture segmentation. Hence, OBIA as synonym of image-object-based image analysis is a tautology, in contrast with spatial context-insensitive (pixel-based) 1D image analysis.

A second critical consideration is that acronym GEOBIA, originally introduced to emphasize EO-IU applications for GIScience, is erroneous, which means misleading at best. If it reads as "image analysis based on geographic objects in the image-domain", then it is a contradiction in terms because no image-object in the image-domain features geographic coordinates pertaining to the scene-domain. If it reads as "image analysis based on geographic objects in the scene-domain", then it is a contradiction in terms because vision means scene-from-image reconstruction and understanding and not vice versa, although psychophysics proved that vision combines inductive/bottom-up with deductive/top-down inference (Vecera and Farah, 1997).

A third critical consideration is that the OBIA/GEOBIA paradigm (Benz *et al.*, 2004; Blaschke and Lang, 2006; Blaschke *et al.*, 2014; Hay and Castilla, 2008; Lang and Blaschke, 2006) comprises a mandatory image segmentation first stage, but it lacks spatial topology-preserving constrains to make an inherently ill-posed image-object-based classification second stage better posed for numerical solution and consistent with human visual perception. In the OBIA/GEOBIA paradigm, a second-stage classifier was let free to be implemented as either (i) a 2D topology-preserving image analysis approach, where primary spatial topological and spatial non-topological information components are fully exploited together with secondary color information, or (ii) a segment-specific 1D image analysis approach, which is spatial topology-non-preserving. The latter is in contrast with the true-fact that spatial information dominates color information in vision and with the well-known fact that the brain's organizing principle is topology-preserving feature mapping (Feldman, 2016), including 30 visual areas or so in primates, e.g., V1, V2, V3, MT and V4, with various degree of retinotopy (Tsotsos, 1990). Unfortunately, in the RS common practice, the vagueness of the original OBIA/GEOBIA paradigm has fostered the ever-increasing development by the GEOBIA community of "easy" spatial context-sensitive 1D image analysis approaches, where spatial topological information is completely ignored, see Figure 8, rather than urging the development of "difficult" 2D image analysis approaches where primary spatial topological and spatial non-topological information components are fully exploited together with secondary color information, see Figure 7.

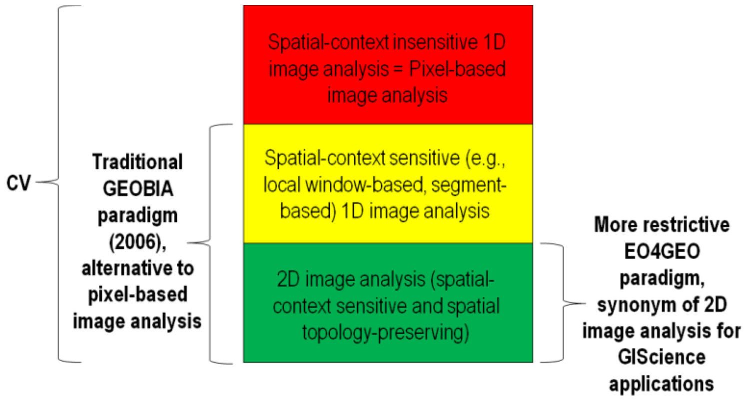


FIGURE 8. *The proposed EO4GEO paradigm is more restrictive than the traditional GEOBIA paradigm, proposed in 2006 as a viable alternative to pixel-based image analysis. EO4GEO is synonym of 2D image analysis for GISCience applications.*

3. Discussion and conclusions

Following the critical appraisal of acronyms OBIA/GEOBIA proposed in Chapter 2 based on unequivocal true-facts about biological vision and primate visual perception, the GEOBIA community is strongly recommended to reconsider the relevance of acronyms OBIA/GEOBIA. Acknowledged that "science progresses one funeral at a time" (Axios, 2017), to successfully cope with EO big data analytics characterized by the five Vs of volume, velocity, variety, veracity and value, the GEOBIA community is encouraged to gather sufficient intellectual fortitude to change its own name into a more exact one, such as EO for GIScience (EO4GEO, EO4GIScience), meaning EO big data analytics in operating mode for GIScience applications, constrained by 2D (retinotopic, topology-preserving) image analysis in cognitive science (2D-EO4GEO), see Figure 8.

References

Axios (2017). Artificial intelligence pioneer, Geoffrey Hinton, says we need to start over, Sept. 15, 2017. Date: 8 Jan. 2018. [Online] Available: https://www.axios.com/artificial-intelligence-pioneer-says-we-need-to-start-over-1513305524-f619efbd-9db0-4947-a9b2-7a4c310a28fe.html

Baatz, M., and Schäpe, A. (2000). Multiresolution Segmentation: An Optimization Approach for High Quality Multi-Scale Image Segmentation, In Angewandte Geographische Informationsverarbeitung XII; Strobl, J., Ed.; Herbert Wichmann Verlag: Berlin, Germany, 58, 12–23.

Baraldi, A. (2017). Pre-processing, classification and semantic querying of large-scale Earth observation spaceborne/airborne/terrestrial image databases: Process and product innovations. Ph.D. dissertation, University of Naples "Federico II", Department of Agricultural Sciences, Italy. DOI: 10.13140/RG.2.2.25510.52808. https://www.researchgate.net/publication/317333100_Pre-processing_classification_and_semantic_querying_of_large-scale_Earth_observation_spaceborneairborneterrestrial_image_databases_Process_and_product_innovations

Benz, U., Hofmann, P., Willhauck, G., Lingerfelder, I. & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS International Journal of Photogrammetry and Remote Sensing, 58, 239-258.

Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Feitosa, R. Q., Van der Meer, F., Van der Werff, H., Van Coillie, F. and Tiede, D. (2014). Geographic Object-based Image Analysis: A new paradigm in Remote Sensing and Geographic Information Science. International Journal of Photogrammetry and Remote Sensing, 87, 180-191.

Blaschke, T. and Lang, S. (2006). Object based image analysis for automated information extraction-a synthesis. Measuring the Earth II ASPRS Fall Conference, 6-10.

Canny, J. (1986). A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell., 8(6): 679–698.

Capurro, R., and B. Hjørland. (2003). The concept of information." Annual Review of Information Science and Technology 37: 343-411.

Cimpoi M., Maji, S., Kokkinos, I., and Vedaldi. A. (2014). Deep filter banks for texture recognition, description, and segmentation. CoRR, abs/1411.6836.

DiCarlo, J. (2017). Keynote: The Science of Natural intelligence: Reverse engineering primate visual perception, CVPR17.

Feldman, J. (2016). The neural binding problem(s), Cogn. Neurodyn., 7, 1-11.

Frintrop, S. (2011). Computational visual attention, in Computer Analysis of Human Behavior, Advances in Pattern Recognition, A. A. Salah and T. Gevers, Eds,. Springer.

Group on Earth Observation / Committee on Earth Observation Satellites (GEO-CEOS). (2010). A Quality Assurance Framework for Earth Observation, version 4.0. http://qa4eo.org/docs/QA4EO_Principles_v4.0.pdf

Hay, G. and Castilla, G. (2008). Geographic object-based image analysis (GEOBIA): a new name for a new discipline. In: Blaschke, T., Lang, S. & Hay, G. (eds.) Object-based Image Analysis: Spatial Concepts for Knowledge-driven Remote Sensing Applications. Berlin: Springer.

Haralick, R. and Shapiro, L. (1985). Image segmentation techniques, Comput. Vision, Graph. Image Process. 29: 100-132.

Horowitz, S., and Pavlidis, T. (1974). Picture segmentation by a directed split and merge procedure, Proc. ICPR, Denmark, pp.424-433.

Hubel, D., and Wiesel, T. (1959). Receptive fields of single neurons in the cat's striate cortex," Journal of Physiology, vol. 148, pp. 574–591.

Iqbal, Q. and Aggarwal, J. K. (2001). Image retrieval via isotropic and anisotropic mappings, in Proc. IAPR Workshop Pattern Recognit. Inf. Syst., Setubal, Portugal, Jul., 2001, pp. 34–49.

Jain, A., and Healey, G. (1998). A multiscale representation including opponent color features for texture recognition," IEEE Trans. Image Proc. 7(1): 124-128.

Kandel, E., Schwartz, J., Eds. (1991). Principles of Neural Science, Appleton and Lange: Norwalk, CT, USA; pp. 441–466.

Ketting, R. and Landgrebe, D. (1976). Classification of multispectral image data by extraction and classification of homogeneous objects. IEEE Trans. Geosci. Electron. vol. GE-14, pp., 19-26.

Lang, S. and Blaschke, T. (2006). Bridging remote sensing and GIS–What are the main supportive pillars? In: LANG, S., SCHÖPFER, E. & BLASCHKE, T., eds. Proceedings of the 1st International Conference on Object-based Image Analysis, 2006 Salzburg. ISPRS, 4-5.

Marcus, G. (2018). Deep Learning: A Critical Appraisal. arXiv: 1801.00631. Accessed: 16 Jan., 2018. https://arxiv.org/ftp/arxiv/papers/1801/1801.00631.pdf

Matsuyama, T. and Hwang, V. (1990). SIGMA – A Knowledge-based Aerial Image Understanding System. New York, NY: Plenum Press.

Cherkassky, V. and Mulier. F. (1998). Learning from Data: Concepts, Theory, and Methods. New York, NY: Wiley.

Nagao, M. and Matsuyama, T. (1980). A structural analysis of complex aerial photographs, New York, Plenum Press.

Ohlander, R., Price, K., Reddy Raj, D. (1978). Picture segmentation using a recursive region splitting method, Computer Graphics and Image Processing. 8 (3): 313–333.

Pessoa, L. (1996). Mach Bands: How Many Models are Possible? Recent Experimental Findings and Modeling Attempts. Vision Res., 36(19), 3205–3227.

Poggio, T. (2012). The Levels of Understanding framework, revised. Computer Science and Artificial Intelligence Laboratory, Technical Report, MIT-CSAIL-TR-2012-014, CBCL-308.

Quinlan, P. (2012). Marr’s Vision 30 years on: From a personal point of view. Perception, 41: 1009 – 1012.

Smith, S. M. and Brady, J. M. (1997). SUSAN - a new approach to low level image processing. Int. J. of Computer Vision, 23(1), 45--78.

Trimble (2015). eCognition® Developer 9.0 Reference Book.

Tsotsos, J. K. (1990). Analyzing vision at the complexity level. Behavioral and Brain Sciences 13: 423-469.

Vecera, S., and Farah, M. (1997). Is visual image segmentation a bottom-up or an interactive process?. Percept. Psychophys., 59, 1280–1296.

Yang, C., Huang, Q., Li, Z., Liu K. & Hu, F. (2017). Big Data and cloud computing: innovation opportunities and challenges, International Journal of Digital Earth. 10:1, 13-53, DOI: 10.1080/17538947.2016.1239771.

Yellott, J. (1993). Implications of triple correlation uniqueness for texture statistics and the Julesz conjecture. Optical Society of America, 10(5), 777-793.