Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 67 (2018) 374 – 379
www.elsevier.com/locate/procedia

11th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME'17

Disruptive data visualization towards zero-defects diagnostics

Luís Ferreira[b], Goran D. Putnik*[a], Nuno Lopes[b], Wiley Garcia[b], Maria M. Cruz-Cunha[b], Hélio Castro[b], Maria L. R. Varela[a], João M. Moura[b], Vaibhav Shah[a], Cátia Alves[c], Zlata Putnik[c]

[a]*Dept. of Production and Systems, School of Engineering, University of Minho, 4804-533 Guimarães, Portugal*
[b]*IPCA - Polytechnic Institute of Cávado and Ave, Vila Frescaínha S. Martinho, 4750-810 Barcelos, Portugal*
[c]*Centro ALGORITMI, University of Minho, 4804-533 Guimarães, Portugal*

* Corresponding author. Tel.: +351-253-510-170; fax: +351-235-510-139. *E-mail address:* putnikgd@dps.uminho.pt

Abstract

Innovative processes become available due to the high processing capacity of emergent infrastructures, such as cloud and ubiquitous computing and organizational infrastructures and applications. However, these intense computation processes are difficult to follow, where co-decision is required, for which the existence of disruptive visualization and collaboration tools that offer a visual tracing capacity with integrated decision supporting tools, are critical for its sustainable success.
This project proposes: a) *a set of immersive and disruptive visualization tools*, supported by virtual and augmented reality, that enables a global perspective of any production agents; b) *a data analytics tool* to complement and assist the decision making; c) *a resource federated network* that allows the brokering and interaction between all existing resources; and d) a *dynamic context-aware dashboard*, to improve the overall productive process and contribute to intelligent manufacturing systems.
The application domain addressed is Zero-Defects Diagnostics in manufacturing as well as in Industry 4.0 in general.

Keywords: Disruptive data visualization, Zero-defects diagnostics, Manufacturing systems, industry 4.0, IoT.

1. Introduction

Advanced manufacturing initiatives, such as recently launched Industry 4.0 initiative, focus achieving zero product defects throughout the manufacturing process. Accepting (Wang, Wang, Mohammed, & Givehchi, 2017) perspectives that reducing defects (towards Zero Defects Manufacturing) may be obtained through the improvement of the manufacturing process through a closed cycle on maintenance operations, including strategies like: data acquisition using intelligent sensors system, signal processing, diagnosis through data mining and knowledge discovery, prognostic assessment with clear defect information and advice, and maintenance scheduling with manufacturing adaptation and optimization control; allow Zero Defects Diagnostics to go further. Having these diagnostics could mean several things. One of them is related to maintenance, meaning that if critical problems occur it will not require a corrective maintenance. Another could be using disruptive visualization to close the cognitive gap in perception of meaning of data, i.e., to have "zero defect diagnostics" of meaning of data. It is our perspective that this can be obtained under advanced contexts of integrated Generative Data Visualization, for example (Kireeva et al., 2012) and Pragmatics (Putnik & Cruz-Cunha, 2007) as main add-ons for getting efficiency and effectiveness on expected large and complex data, as for example data on complex production networks and inevitable manufacturing communities, as well as on data of other manufacturing system concepts.

This paper presents some cases which need disruptive visualizations, adjacent to Zero Defects Diagnostics manufacturing services. A general framework for disruptive data visualization is given, that involves technological based components, as well as Pragmatics renderers (Luís Ferreira et al., 2017). A demonstration explores a virtual reality solution applied to automobile engine industry.

doi:10.1016/j.procir.2017.12.270

2. Related work in data visualization to zero-defects diagnostics

New innovations, devices, technologies and their new contexts contribute to new minds and new needs, letting us act not only as a viewer but as an actuator and data producer, instead. Being aware of it can radically and quickly change the perspective and capacity to deal with known and unknown existing data.

This capacity to better and efficiently discover and use existing data, represents a critical add-on on emergent required decision systems. Visual representations translate data into a visible form that highlights features, including commonalities and anomalies more quickly, enabling a faster and more focused analytical reasoning process (Thomas & Cook, 2005). The full digitalization coming from Industry 4.0 represents a high heterogeneity, relevance and sovereignty (Kautzsch, Krenz, & Sitte, 2016) of complex data scenarios, dictating the emergent concerns of decision-makers.

The arising of: i) high (local and distributed) capacity of processing (multiple cores, dedicates graphics, others); ii) innovative processing libraries and algorithms (dashboards, graphics, vision, others); and iii) advanced visualization devices (VR, AR, others) supporting immersive environments (Yang, Huang, Li, Liu, & Hu, 2017), represent technological issues and extraordinary facilitators for data discovery, visualization, analysis and decision. Following previous ambitious forecasts (Sackett, Al-Gaylani, Tiwari, & Williams, 2006), nowadays ICT can definitely support most of the announced requirements then.

However, this new capacity of data visualization, even called disruptive, is not only a mere technical issue. The expected new actors (coming from IoT and Industry 4.0) on data generation (sensors), acquisition (cloud) and correlation (artificial Intelligence) sustains an uncommon huge amount of data that requires innovative capacity to analyze it. A clear paradigm shift deals now with data from multiple and distinct sources, from science, to social and humanities (Kitchin, 2014). The knowledge base on applied research is now reinforced by continuous knowledge coming from data mining and processing. A new epistemology arises, where binomial object-knowledge behaves as never before with mutual, dynamic and accomplice relations (…) 'the end of theory', the creation of data-driven rather than knowledge-driven science, and the development of digital humanities and computational social sciences that propose radically different ways to make sense of culture, history, economy and society (…) (Kitchin, 2014).

Although Virtual and Augmented Reality technologies are more than 30 years old, their use in industry has expanded over the past decade, due to the increased performance of hardware systems and human-computer interface devices. The supporting technology and software are mature, stable, and, most importantly, usable (Berg & Vance, 2017). Immersive Data Visualization using Virtual Reality is already being explored (Sackett et al., 2006) and several Industry 4.0 initiatives already follow advanced visualization strategies (Roy, Stark, Tracht, Takata, & Mori, 2016), (Qian, Tu, & Lou, 2017), as well as other Exponential Technologies (additive manufacturing, nanotechs, etc.) (Fig. 1). However, these strategies were essentially technological based and thus, serious problems on systems interoperability will arise, surely (Ferreira, L., 2013). Although accepting that the human factor is aligned with these transformations, in fact, most of the solutions still interact with completely passive users, being not yet prepared for the effective users' collaboration, co-construction and co-decision.

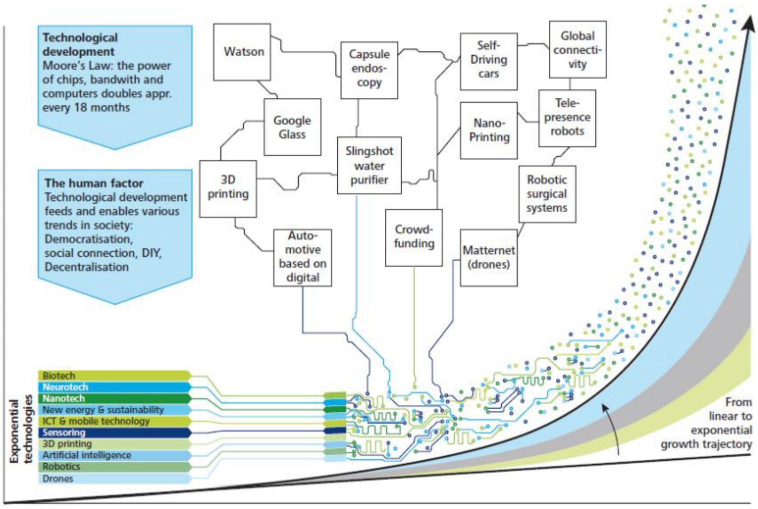

Fig. 1. Industry 4.0 emergent exponential technologies (Schlaepfer, Koch, & Merkofer, 2015).

3. Some examples for disruptive data visualization in I4.0

Early diagnostics and on-the-fly data are essential for timely correct decisions. The continuous or preventive maintenance (Roy et al., 2016) (Garcia, 2016) moves to predictive maintenance.

The Fig. 2 shows the visualization of a real-time monitoring of manufacturing processes and real-time simulation processes in a cyber physical system (CPS). The figure shows multiple windows in which the data are continuously scrolling, one window per CPS element. In a CPS we can have tens, hundreds, thousands or even millions of elements, and corresponding windows. When looking at this data it is easy to see the difficulty to analyze and correlate those results. Obviously, we need some disruptive data visualization to close the cognitive gap.

As another example, from the formal language representation, consider a phrase in a context-free language,

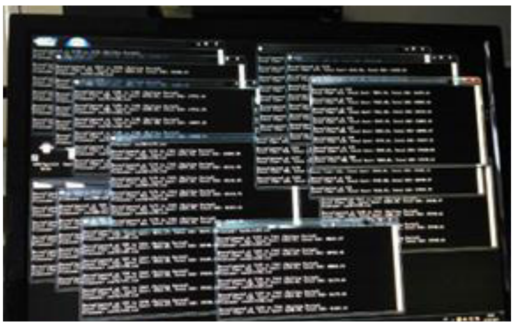

Fig. 2. Windows representing CPS element's raw data.

"c[r[cc[r[c[r[cc]]c]]]r[c[r[ccc[r[cc]r[c]]]]]r[ccc[r[c]]]]"

The corresponding context-free grammar rules, that generated this language are {S → c[A]; A → AA; A → r[B]; B → c[A]; B → BB; B → c}. However, it is difficult to verify, just by looking at the string whether the phrase belongs to the above-mentioned grammar. It requires a careful observation and calculation to conclude whether the phrase belongs to the grammar or not. Now consider the structural description (Levy & Joshi, 1978), or skeleton, of the same phrase (Fig. 3). It is easier to see the underlying structure of the phrase and verify whether the phrase follows the syntax definition provided by the given grammar. The figure was generated through a software developed in order to study context-free grammar synthesis (Shah, 2015) and the graphical representation made the experiments much easier. Further tools could be developed that provide more effective form of representation and analysis of complex data structures like the one referred here.

It is clear that a structural description, however simple and useful for a grammar inference task, and eventually clear in its representation to an expert, cannot be understood intuitively without a detailed description attached to it, and may appear as a complex system itself.

However, even with this visualization of structural data, it is very difficult to perceive if it represents the corresponding grammar. Obviously, we need some further disruptive data visualization to close the cognitive gap.

The capacity to classify and correlate results should be essential and thus possible to create distinct outputs or visualizations. The Fig. 4 shows a possible web graph advanced visualization, virtually a disruptive visualization, representing web pages as nodes and hyper-text links as weighted edges inter-connecting nodes (Hendler, Shadbot, Hall, Berners-Lee, & Wietzner, 2008). In the context of I4.0, it is possible to imagine this visualization to be used for visualizing data of complex production networks, Internet of Things, or CPS.

However, in the case of a huge amount of calculus or results, the amalgam of disparate outputs should result imperceptible.

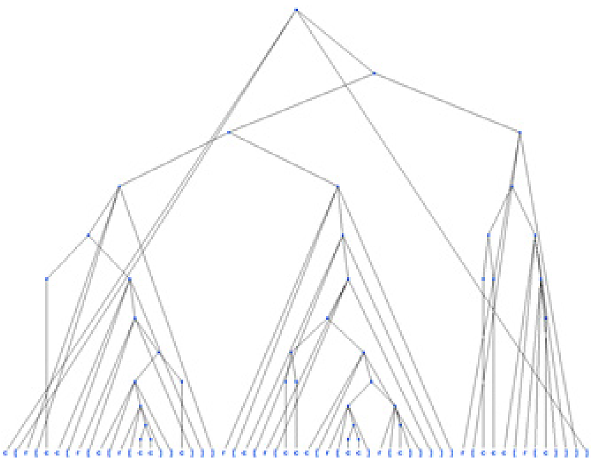

Fig. 3. A visualization of structural description of a phrase, for context-free grammar inference task.

Fig. 4. Web graph representation (Hendler et al., 2008).

4. Architecture for supporting disruptive visualization for zero defect diagnostics

There are many advanced solutions based on several independent and uncoupled information systems that require specific and complex middleware for assuring their interoperability (Fig. 5). The user participation is passive so it must follow the wizards of each system.

The possibility to deal with uncertainty or complexity is supported by integrating other systems, if possible, timely and usefully.

Data visualization, which is aligned with emergent technologies and devices, must be seen nowadays not only as advanced dashboards and interaction devices, but as a set of fully integrated services that makes the data visualization the key part of a whole decision-maker tol, instead. The capacity to: a) get different and useful data visualization and interpretation according to the current context (user's information-field and expertise, data relevance, others); b) assure efficiency and effectiveness on that visual data analysis using Pragmatics on co-decision; and c) the integration of several other "tools" like advanced dashboard services, Federated Networks (FN) and immersive data visualization with virtual reality, represents a global framework that sustains a disruptive data visualization towards an innovative Generative Visualization.

In a scenario of big data (complement to Industry 4.0), the possibility to enrich user interfaces with: a) Advanced dynamic

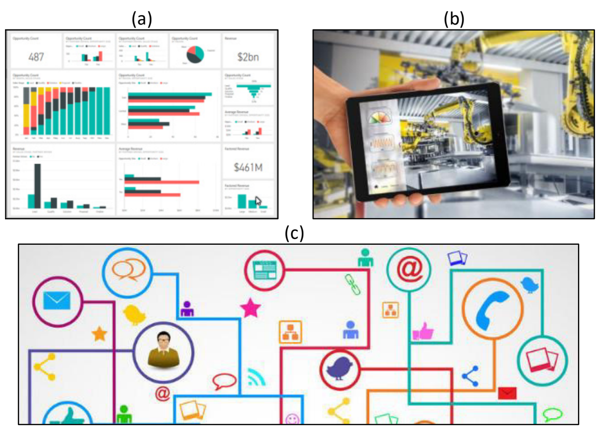

Fig. 5. Actual uncoupled systems architecture: (a) Dashboards; (b) VR; (c) Collaborators.

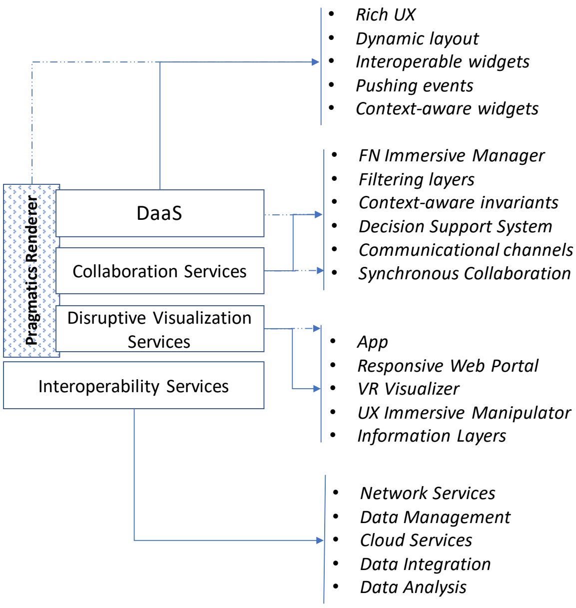

Fig. 8. Zero-defects diagnostic integrated logical supporting architecture.

context-aware dashboards; b) Social Federated Networks to co-decision support; c) Several integrated Data Analytics tools; and d) Immersive Visualization Tools, represents a DaaS (*Desktop as a Service*) supporting truly effectiveness and, as a whole, an important tool for advanced decisions support, as shown in Fig. 8**Error! Reference source not found.**.

Actual dashboards are mere platforms for visually organizing distinct and no interoperable widgets. Basically, events from a widget do not influence the behaviour of another widget. Our dashboard has mechanisms for dynamic integration of any widget, representing any application, as well as a synchronization mechanism with external sources of data or events. If an event happened somewhere, a pushing architecture publishes that event for all that subscribe it, and a global dynamic dashboard reconfiguration is immediate!

Since co-decision and co-creation is essential to grant effectiveness (L Ferreira, Putnik, Lopes, Lopes, & Cruz-Cunha, 2015), the capacity to efficiently discover and manage all related resources (technicians, machines, materials, etc.), agile context-aware brokering and synchronous communication tools are required. In addition to a social based platform, the federated network offers an advanced searching and interaction tool over an ecosystem of existing resources. A Pragmatics renderer will support human-to-human natural. We believe that the more capacity to share knowledge, the more add-value exists.

Since there are several powerful data related (analytics, modelling, mining, etc.) processing tools (SPSS, Pentaho, KNime, Augustus, etc.), the possibility to get all them fully integrated and synchronized is essential. Thus, ensuring interoperability to share a data model between those systems, is critical and expected, having, for instance, PMML (Predictive Model Markup Language) as a supporting base.

The use of Virtual Reality technologies and devices (Oculus Rift, Daydream, etc.) (Donalek et al., 2014) for data visualization, will allow visual deep data analysis (Strelcov, Belianinov, Sumpter, & Kalinin, 2014) on existing data models.

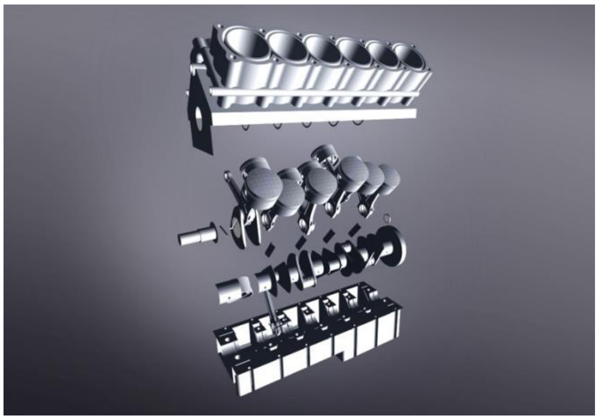

Fig. 6. Engine components - original 3D model available at https://grabcad.com/library/v12-engine--1.

Getting knowledge from a huge set of unstructured data or any kind of intelligence from unknown related data, is the main challenge. These kinds of devices allow decision-makers to immerse on existing data, offering a new and more natural perspective of that data and, using their experience and expertise, to find things that are unknown beforehand, to recognize patterns, to identify correlations, to expose hidden trends and dive deep over unknown related data.

5. A demonstration example for the automotive industry

As a demonstration, we present the visualization of an automotive engine. The Fig. 6 shows the components of an engine scattered apart for easy visualization. To reach zero defects diagnostics, we propose to analyse data visually with annotated information tags that provide additional information and enable the detection of defect situations that are otherwise stored as analytical data of difficult comprehension and limited if not even none visualization, since the static visualization of scattered components do not reveal real-time conditions that can contribute to defects.

The Fig. 7 shows a 3D visualization of the same engine components but with additional geospatial information tags that reveal non-conforming conditions that may be the beginning of defects. These conditions are evaluated by advanced decision support systems (based on data analytics tools) that create the

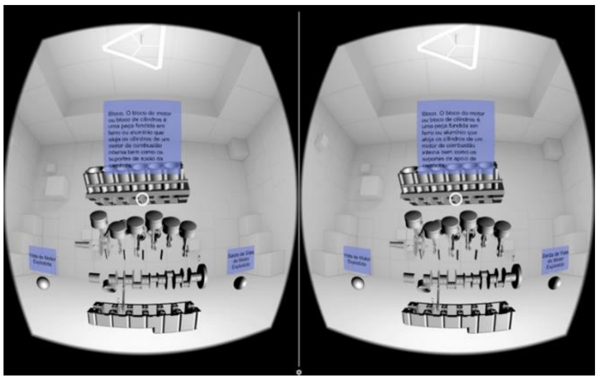

Fig. 7. VR data visualization with annotation tags, developed by research students Filipe Coelho and André Machado.

visible annotation tags at the most relevant points in the 3D space.

When inside a virtual reality environment, we have the possibility to navigate inside the 3D space, and zoom in into specific areas of interest. This navigation technology enables users to verify models within a high level of accuracy and detail. There is also the possibility to add layers of information like visual markers to identify critical areas, as shown in Fig. 9. Head mounted display hardware, like the Oculus Rift and HTC Vive, are coupled with hand controllers that allow users to have more control over the virtual environment with simple natural gestures, trigger button actions and multidimensional axis interfaces. Also, these hand controllers allow users to highlight specific rigid body component parts of the 3D components, and zoom in into minimal space areas that could be difficult to reach in other simulation scenarios. And because virtual reality allows the user to look in all directions and updates the user's viewpoint by passively tracking head motion, interaction is facilitated as it would be if we manipulated real component parts. In fact, users with a VR interface complete a search task faster than users with a stationary monitor and a hand-based input device (Pausch, Proffitt, & Williams, 1997). Although virtual reality has generated a lot of enthusiasm, there is still a long way to go at the user's interaction level, such as grabbing and dragging objects, or even touching virtual dashboard interfaces, as many gesture based solutions still do not work reliably, whereas controller based methods are not as natural as hand pose recognition (Lin, Schulze, San, & Jolla, 2016).

6. Conclusion

In this paper, we discuss how new data visualization techniques and collaboration tools can be used to enhance the visualization of a production line, facilitating the analysis of the system through visual enhancements that will contribute to an improved decision making towards an effective zero-defect diagnostics approach. Specifically, an architecture for supporting zero defects diagnostics combines context-aware dashboards, federated resource networks, data analytics and immersive visualization tools.

Industry 4.0 will need disruptive visualization for IoT, Cyber-Physical Systems, large and complex production networks and collaborative engineering. The architecture proposed in this paper is suitable for supporting these requirements to face the challenges of the future manufacturing paradigms.

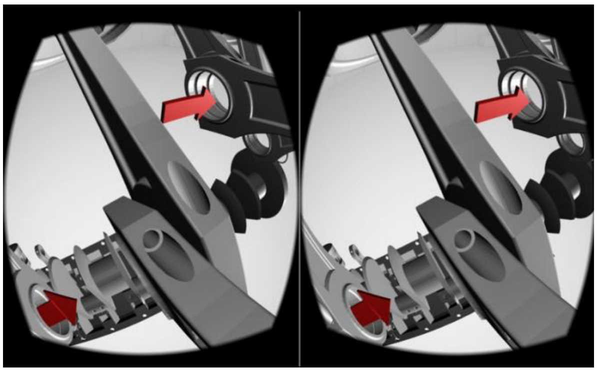

Fig. 9. VR high level detailed visualization inside a motor engine, with red markers placed in critical areas.

Acknowledgements

This work has been supported by (1) COMPETE: POCI-01-0145-FEDER-007043 (2) FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2013, (3) Ph.D. Scholarship Grant reference SFRH/BD/85672/2012, and (4) Ph.D. Scholarship Grant reference SFRH/BD/62313/2009.

References

Berg, L. P., & Vance, J. M. Industry use of virtual reality in product design and manufacturing: a survey. *Virtual Reality*, 2017, *21*(1), 1–17. https://doi.org/10.1007/s10055-016-0293-9

Donalek, C., Djorgovski, S. G., Davidoff, S., Cioc, A., Wang, A., Longo, G., … Drake, A. Immersive and Collaborative Data Visualization Using Virtual Reality Platforms, 2014. https://doi.org/10.1109/BigData.2014.7004282

Ferreira, L. *Architectures for Integration of Information Systems under conditions of Dynamic Reconfiguration of Virtual Enterprises*. *Production Systems*., 2013, University of Minho

Ferreira, L., Putnik, G., Cunha, M. M. C.-, Putnik, Z., Castro, H., Alves, C., … Varela, L. A Cloud-Based Architecture with embedded Pragmatics Renderer for Ubiquitous and Cloud Manufacturing. International Journal of Computer Integrated Manufacturing, 2017, 30(4–5), 483–500. https://doi.org/10.1080/0951192X.2017.1291995

Ferreira, L., Putnik, G. D., Lopes, N., Lopes, A., & Cruz-Cunha, M. M. A Cloud and Ubiquitous Architecture for Effective Environmental Sensing and Monitoring. In Procedia Computer Science, 2015. https://doi.org/10.1016/j.procs.2015.09.240

Garcia, W. da S. Modelo de Gestão de Ativos em Tempo Real. 2016, Universidade do Minho.

Hendler, J. a, Shadbot, N., Hall, W., Berners-Lee, T., & Wietzner, D. Web science: an interdisciplinary approach to understanding the web. Communications of the ACM, 2008, 51(7), 60–69. https://doi.org/http://doi.acm.org/10.1145/1364782.1364798

Kautzsch, T., Krenz, W., & Sitte, T. Digital Industry - The true value of industry 4.0., 2016, Oliver Wyman.

Kireeva, N., Baskin, I. I., Gaspar, H. A., Horvath, D., Marcou, G., & Varnek, A. Generative Topographic Mapping (GTM): Universal tool for data visualization, structure-activity modeling and dataset comparison. Molecular Informatics, 2012, 31(3–4), 301–312. https://doi.org/10.1002/minf.201100163

Kitchin, R. Big Data, new epistemologies and paradigm shifts. Big Data & Society, 2014, 1(1), 205395171452848. https://doi.org/10.1177/2053951714528481

Levy, L. S., & Joshi, A. K. Skeletal structural descriptions. Information and Control, 1978, 39(2), 192–211. https://doi.org/10.1016/S0019-9958(78)90849-5

Lin, J., Schulze, J. P., San, C., & Jolla, L. Towards Naturally Grabbing and Moving Objects in VR. The Engineering Reality of Virtual Reality, 2016, 1–6. https://doi.org/10.2352/ISSN.2470-1173.2016.4.ERVR-415

Pausch, R., Proffitt, D., & Williams, G. Quantifying Immersion in Virtual Reality. In Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques, 1997, (pp. 13–18). New York, NY, USA: ACM Press/Addison-Wesley Publishing Co. https://doi.org/10.1145/258734.258744

Putnik, G. D., & Cruz-Cunha, M. M. Knowledge and Technology Management in Virtual Organizations, 2007, IDEA Group Publishing.

Qian, X., Tu, J., & Lou, P. A general architecture of a 3D visualization system for shop floor management. Journal of Intelligent Manufacturing, 2017, https://doi.org/10.1007/s10845-017-1335-1

Roy, R., Stark, R., Tracht, K., Takata, S., & Mori, M. Continuous maintenance and the future – Foundations and technological challenges. CIRP Annals - Manufacturing Technology, 2016, 65(2), 667–688. https://doi.org/10.1016/j.cirp.2016.06.006

Sackett, P. J., Al-Gaylani, M. F., Tiwari, A., & Williams, D. A review of data visualization: opportunities in manufacturing sequence management. International Journal of Computer Integrated Manufacturing, 2006, 19(7), 689–704. https://doi.org/10.1080/09511920500504578

Schlaepfer, R., Koch, M., & Merkofer, P. Industry 4.0. Challenges and solutions for the digital transformation and use of exponential technologies. Retrieved October 26, 2016, from https://www2.deloitte.com/tw/en/pages/manufacturing/articles/industry4-0.html

Shah, V. H. Contribution to automatic synthesis of formal theories of production systems and virtual enterprises, 2015, University of Minho.

Strelcov, E., Belianinov, A., Sumpter, B. G., & Kalinin, S. V. Extracting physics through deep data analysis. Materials Today, 2014, 17(9), 416–417. https://doi.org/10.1016/j.mattod.2014.10.002

Thomas, J. J., & Cook, K. A. Illuminating the path: The research and development agenda for visual analytics. IEEE Computer Society, 2005, 184. https://doi.org/10.3389/fmicb.2011.00006

Wang, X. V., Wang, L., Mohammed, A., & Givehchi, M. Ubiquitous manufacturing system based on Cloud: A robotics application. Robotics and Computer-Integrated Manufacturing, 2017, https://doi.org/10.1016/j.rcim.2016.01.007

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