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.

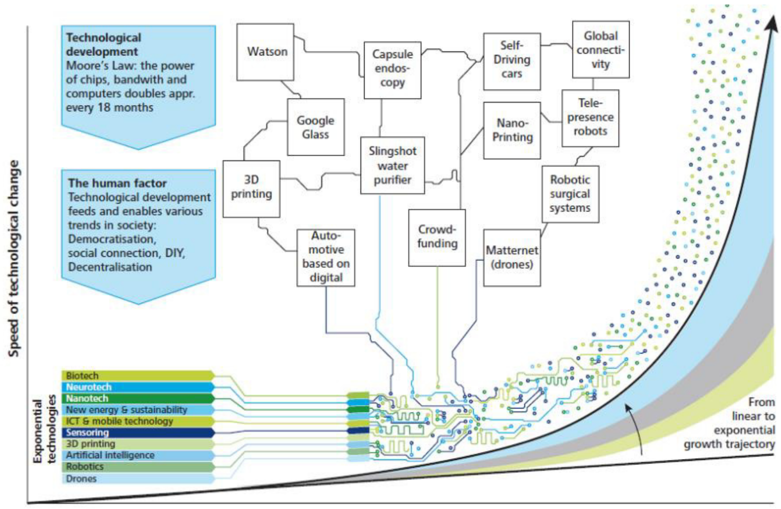

Fig. 1. Industry 4.0 emergent exponential technologies (Schlaepfer, Koch, & Merkofer, 2015).

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.

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,

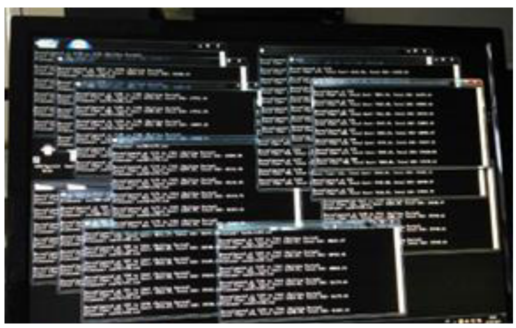

Fig. 2. Windows representing CPS element's raw data.