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Internet of Things – Enabled Visual Analytics for Linked Maintenance and Product Lifecycle Management

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Abstract: When closed loop product lifecycle management was first introduced, much effort focused on establishing ways to communicate data between different lifecycle phase activities. The concept of a smart product, able to communicate its own identity and status, had a key role to play to this end. Such a concept has further matured, benefiting from internet things-enabled product lifecycle management advancements. Product data exchanges can now be brought closer to the point of end use consumption, enabling users to become more proactive actors within the product lifecycle management process. This paper presents a conceptual approach and a pilot implementation of how this can be achieved by superimposing middle of life relevant product information to beginning of life product views, such as a 3D product CAD model. In this way, linked maintenance data and knowledge become visual features of a product design representation, facilitating a user's understanding of middle-of life concepts, such as occurrence of failure modes. The proposed approach can be particularly useful when dealing with product data streams as a natural visual analytics add-in to closed loop product lifecycle management.

Keywords: Internet of Things; Visual Analytics; Maintenance; Product Lifecycle Management

1. INTRODUCTION

Internet of things (IoT) -enabled products lend themselves to closing information loops between different product lifecycle phase activities (Kiritsis, 2011), implementing the early vision of closed loop product lifecycle management (PLM) between beginning of life (BOL), middle of life (MOL), and end of life (EOL) activities (Kiritsis *et al*., 2003). As a result, relevant research focused on mapping the IoT layered stack to product data exchange modelling for PLM, up to the application layer (Framling *et al.,* 2014). In order to bring product data exchanges closer to the point of consumption by end-user applications, data interoperability along the IoT stack needs to be established. This encompasses both lower level exchanges, such as sensor readings, all the way to higher, application layer information and knowledge (Yoo *et al.,* 2016). Semantic interoperability across connected product internetworking layers has become a key ingredient for closed loop PLM.

From a user viewpoint, product lifecycle data at the application layer are best exchanged with application layer relevant means, for example with visually enhanced product views. This paper presents a conceptual approach to achieve this by superimposing MOL relevant product data to BOL product views, such as a 3D product CAD model. In this way, linked maintenance data become visual features of a product design representation, facilitating the design-side understanding of MOL concepts, such as failure modes. Such an approach can be useful when dealing with real data streams from products as a natural visual analytics extension to closed loop PLM. The rest of the paper is structured as follows. Section 2 places the current research against the backdrop of related work in the field. Section 3 outlines the overall concept of visual analytics through blended application layer product representations. The concept is implemented on a laboratory based test rig and details are provided in section 4. Section 5 offers a conclusion, and outlines future research paths.

2. RELATED WORK

2.1 Product Lifecycle Management Data Flows

In early research efforts, which introduced the concept of closed loop PLM (Kiritsis *et al*., 2003), much attention was placed on establishing ways to communicate data between different lifecycle phase activities (Jun *et al.,* 2007). Physical aspects of such exchanges were handled with radio frequency identification (RFID) technology through product embedded information devices (Kiritsis *et al.,* 2008), largely focusing on identification and basic product data. Work in this area converged with the concept of smart products (Meyer *et al.,* 2009) or intelligent assets (Brintrup *et al.*, 2011). With such a concept increasingly becoming mainstream, enhanced products were recognised as key to enabling integration of operations, maintenance, and logistics (VanBelle *et al.*, 2011), as well as monitoring and control functions (Meyer *et al.,* 2009). This in turn required a different level of data exchanges to be established, driving efforts to establishing semantic interoperability of connected systems. As a result further research looked into how semantic (Cassina *et al.*, 2008) and ontology based modelling (Matsokis and Kiritsis, 2010) can achieve this level of product information sharing. This in turn led to establishing appropriate, standardized, and semantically

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enriched data flows within different product lifecycle phase activities (Främling *et al.*, 2013)(Kubler *et al.*, 2015a).

When dealing with integrating MOL with BOL product information, one of the key objectives is to understand already at the design stage how the product will perform and be managed during operations and maintenance. To achieve this, operations and maintenance – related data need to be fed back to design stage PLM activities. Moving beyond asset tracking and lightweight product data exchanges, feeding back such middle of life information can be challenging. Additional concerns are related to the efficiency of the radio frequency (RF) part of the data exchange, as well as increased asset monitoring needs, to accommodate for sensing modalities of considerable bandwidth. Sensor networking protocols, such as those linked to IEEE 802.15.4, have seen early adoption in wireless sensor network applications for asset monitoring (Emmanouilidis and Pistofidis, 2010). The need to process locally acquired information on sensing nodes enabled asset-embedded intelligence beyond tracking and identification (Emmanouilidis, *et al.,* 2009) (Liyanage *et al.*, 2009) to be embedded on sensor board nodes. This expands the ability of asset data exchanges to higher added value embedded data processing (Emmanouilidis and Pistofidis, 2010), featuring some level of product self-awareness (Katsouros *et al.*, 2015). Such level of awareness is aligned with an agent-based view of intelligent assets (Leitão *et al.*, 2013). Thus, monitored assets are empowered to sense, react and even proactively manage their functionality to serve specified objectives.

The confluence of internetworking connectivity, local, distributed and cloud-based computational capabilities, with the ability to semantically enrich product information has therefore emerged as a key enabler for introducing connected and smart products in extended enterprise value chains (Kiritsis, 2011). Product avatars (Wuest *et al.*, 2015), product shadows (Vermesan and Friess, 2016), and digital twins (Vermesan *et al.*, 2011) are all terms employed to describe the digital counterpart of a physical asset, and jointly compose an entity or system, which acts as a smart agent (Leitao *et al.*, 2016) or intelligent product in a cyber-physical world of interconnected assets (Leitao *et al.*, 2016). This capacity of coupling physical assets with digital representations (*Wuest et al.,* 2015) enable substantial advancements in enterprise information systems, increasingly empowered to integrate product data and knowledge (El Kadiri *et al.*, 2016). Furthermore, it elevates the capability to close PLM data loops at higher semantic layers via enriched data and knowledge (Yoo *et al.,* 2016).

Linking data and knowledge produced by human and non-human actors is consistent with the semantic web paradigm of linked data, taking the form of linked product knowledge (Pistofidis *et al.*, 2016)(Kiritsis, 2016). While application layer PLM considerations based on interoperable modelling of product data is aligned with a product-centric viewpoint, a user perspective still needs to be brought in. The concept a user-centric view of Industrie4.0 technology for user augmentation and involvement in production activities has recently gained attention, with terms such as 'Operator 4.0' been used to denote the social nature of human involvement in related production activities (Romero *et al.*, 2017). A key relevant concept is information context management, discussed next.

2.2 Context Fusion and Data Value Chains

The hyper-connected world of products, human actors, and operating environments, enabled by IoT technologies, creates a potential for explosive growth in the generation of product – related data streams. It is not sufficient anymore to seek to integrate such information centrally. Instead, part of the information integration is best performed at the point of data consumption. For such integration to produce meaningful results, the complexity of relevant product information needs to be managed. Directly relevant to establishing efficient architectures, indexing, and big data management capabilities for IoT -generated data is the key concept of context, adopted in context aware computing (Perera *et al.*, 2014). The principle of context information management is that at the point of consumption only contextually relevant information, knowledge and services need to be made available. In asset management, for example, context can be composed by factors quite specific to the application domain. Nonetheless, these may fall under the broad categories of asset, user, business, environment and system context, which at a high abstraction level can be considered as having cross-domain relevance (Emmanouilidis *et al.,* 2013)(Fig. 1). In production environments, contextual relevance is needed to resolve the high variability in the background circumstances, defining the decision making landscape (El Kadiri *et al.*, 2016). Different levels of product related information processing are employed in a product data value chain, wherein at each stage of processing, the data value is enriched through analytics, visualisation, and dedicated application services.

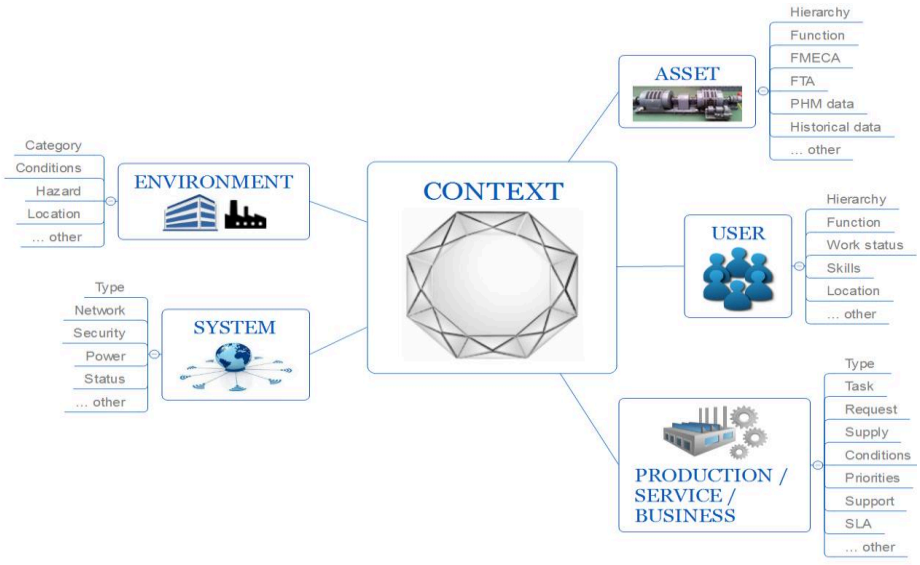

Fig. 1. Context in Asset Management

The enhanced value of product data across such a data value chain justifies the viewpoint that data is to be considered a value adding asset itself (Kubler et al. 2015b). Contextually relevant information management could be viewed as a scaled extension of information fusion in the IoT world (Snidaro *et al.,* 2015). IoT technologies enable to connect human and non – human actors, and therefore integrate the human in the loop of asset and PLM activities. This is a key target for such knowledge-intensive activities (Pistofidis *et al.*, 2016)(Emmanouilidis *et al.*, 2016). The need to deliver context – based product views with application – layer relevant means is linked to context dissemination (Perera *et al.*, 2014). Context dissemination effectively translates context data to actionable context. A natural approach to achieve this is via blended digital product representations, as introduced next.

3. IOT - ENABLED PRODUCT VISUAL ANALYTICS

From the early days of exploratory data analysis (Tuckey, 1962, 1977) till modern day big data analytics (Idreos *et al.,* 2015), part of the power of data analysis lies with the preparatory phase of obtaining different descriptions and representations of data, to enable greater insight. Early computer-based data analysis offered limited ways of user interaction with data. Among the data exploration techniques, visual analytics empowers data analysts with tools to facilitate and steer their expert judgement to visually presented aspects of data characteristics (Thomas and Cook, 2005). Such data views are often easier to comprehend, as human perception naturally favours visual features compared to reviewing raw data (Endert *et al.*, 2014). Bringing the human in the loop is already at the heart of modern PLM tools, offering context-dependent product views, aiding interaction with contextually-relevant product representations. The need for human interaction in via relevant software tools is such that justifies the expression "the human is the loop" (Endert *et al.*, 2014).

Visual analytics employ simple but cognitively powerful ways of embedding semantics in the visual data representations. From a user viewpoint the requirement is to share not only product lifecycle data but to do so with application – layer relevant means: that is via visually enhanced product views. A conceptual approach of how this can be achieved is introduced in this paper. Considering that the most user-friendly product representation is in most cases a 3D product model, the key idea is to employ such a design – stage product representation together with MOL product information, related to product condition monitoring. By superimposing MOL relevant product information to BOL product views, such as a 3D product CAD model, linked maintenance data and knowledge (Pistofidis *et al.*, 2016) become visual features of a product design representation, facilitating a user's understanding of MOL concepts, such as the occurrence of failure modes, within a design viewpoint. The concept is illustrated in (Fig. 2), wherein the target is to link maintenance related data with a design-stage digital product representation. A data processing chain is presented, starting with the initial data generation, comprising the original CAD design for an asset, along with sensor data collected from asset operation. The next step is to process the data so as to extract key features to aid tasks such event detection and diagnostics. Data quality management and data curation is handled at the next stage. The way to manage and store both raw and processed data is handled by the data storage management approach, which may include local and edge node data management, distributed data storage or central repository approaches. Finally, the data is converted to a form relevant to application layer views and user interaction, which may comprise visual analytics and enhanced product views, as discussed in more detail in the next section.

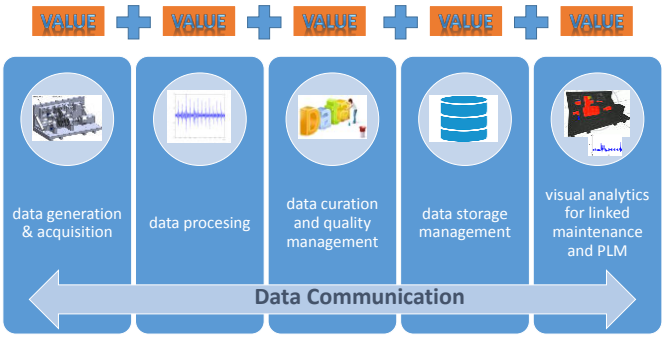

Fig. 2. IoT-enabled product visual analytics value chain

Each processing stage adds value to the data. Thus, the end user application conveys enriched information to the user, facilitating for example the cognitive task of interacting with a PLM tool. While on-the-job activities are known to be effective knowledge triggers, blended lifecycle product representations in PLM can bring some of the on-the-job advantages, carried through interaction with digital product views. This is potentially valuable when dealing with real data streams from IoT – enabled products. It serves as a natural visual analytics extension to closed loop PLM views. The concept of IoT- enabled product visual analytics is quite broad but this paper specifically looks into it as a means to deliver visual analytics for linked knowledge in maintenance and PLM. It is a natural extension to earlier approaches for managing linked knowledge in maintenance (Pistofidis *et al.*, 2016), seeking a direct integration with PLM tools. The next section presents an instantiation of the blended digital product visual analytics on a laboratory testbed arrangement.

4. PILOT IMPLEMENTATION

The concept of blended digital product visual analytics was demonstrated on a laboratory test arrangement. This was a mechanical transmission rig, comprising a motor, a lower shaft with four, 42-tooth gears, driven by a motor, and an upper shaft with one larger 62-tooth gear, which is driven by the first shaft through meshing the upper shaft gear with any of the lower shaft gears (Fig. 3). Loading conditions can be adjusted with a brake, attached to the upper shaft, while the rotational speed is controlled by adjusting the motor speed. The lower shaft gears are initially identical. Defects are introduced to gears 1-3, while keeping one gear in normal condition for reference. The defects are intended to emulate pitting, growing from smaller scale on gear 1 to a level consistent with the end effects of extensive spalling, causing tooth pieces to fall apart (Fig. 4). The aim was to produce an instantiation of the concept of linked knowledge in maintenance and PLM, with knowledge superposition to product views.

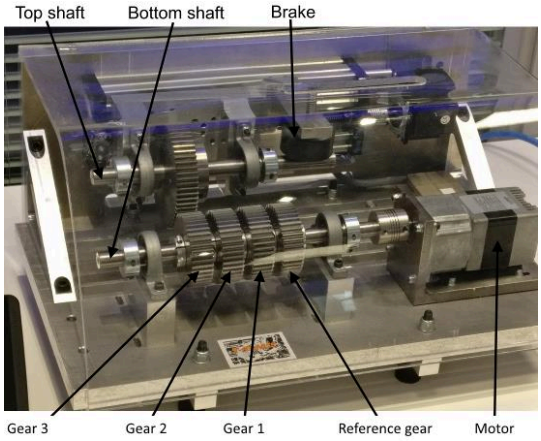

Fig. 3. Gearbox test rig

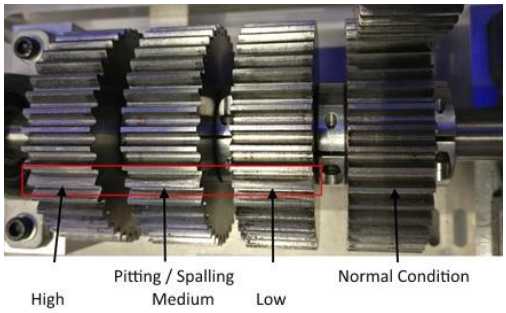

Fig. 4. Defect introduction

To achieve this, a low cost IoT – enabled monitoring solution, implementing data acquisition and basic diagnostics, was introduced. Rather than developing a thorough engineered solution, the demonstration objective focused on instantiating the basic data process chain for the blended digital product visual analytics concept of Fig. 2. This chain comprises

a. data generation process, via a prototype data acquisition
b. a data processing stage, wherein acquired data are converted to monitoring parameters
c. a basic diagnostic stage, wherein acquired parameters are translated into asset conditions
d. blended visual analytics, jointly handling MOL data (e.g. diagnostics) with BOL (3D product model) product views

There is a correspondence between steps 'a'-'d' with the process chain of Fig. 2. Specifically, 'a' and 'b' correspond to the 1st and 2nd stages of the figure. Stage 'c' weakly contributed to stage '3', essentially annotating data with diagnostic information. The 'knowledge outcome' of step 'c' is communicated to the end user, via colouring the part of the CAD design (component, assembly or sub-assembly) with a colour carrying a semantically meaningful metaphor, ie 'red' indicating 'alert' status, if a failure mode is diagnosed on the studied component, leading to triggering an alert.

The data generation process was implemented through an Arduino UNO board and two MPU 6050 accelerometers to capture gearbox vibration (Fig. 5). While this is not a sufficient set up for an industrially relevant solution, it is adequate for demonstrating the proposed concept. The data processing stage was implemented on a Raspberry Pi 3 Model B board on Python, employing the SciPy library. This included signal averaging and extraction of standard statistical parameters from the acceleration signal. These were as in (Katsouros *et al.*, 2015) and comprised the signal RMS, skewness, kurtosis, shape factor, crest factor, peak value and impulse factor. A stream of data acquired in this way are a sequence of vectors $\mathbf{x}_i \in \mathbb{R}^7$: $\mathbf{x}_i = [rms_i, sk_i, k_i, sf_i, cf_i, p_i, if_i]^T$

with $i = 1, \dots, K$, wherein the vector parameters correspond to the parameters described above and K is the number of samples in a data stream. A Fast Fourier Transform (FFT) representation of the vibration signal is also calculated on board, after adequate filtering and windowing. The focus in this paper is not specifically on the condition monitoring functionality but on incorporating the diagnostic outputs in an environment offering a visual analytics view of the product. Any other monitoring setup can be incorporated instead.

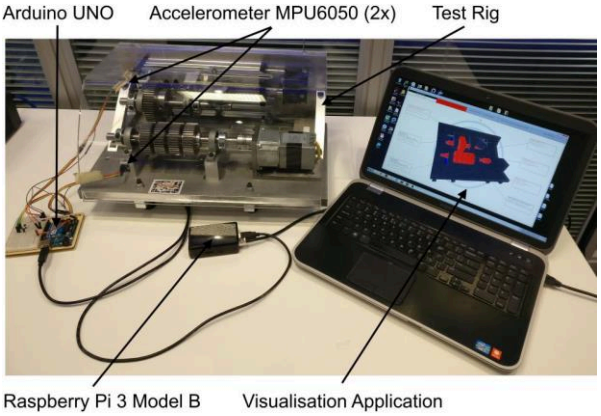

Fig. 5. Experimental setup arrangement on the test rig

An example of the overall test arrangement can be seen in Fig. 5. Reference data acquisition experiments were performed with different gear coupling setups, starting with gear without defects to obtain reference data from normal operating condition. Data were acquired with each one of the other lower shaft gears coupled with the upper shaft gear, to obtain representative samples from a gradual fault progression. The difference between reference samples from normal and progressing fault conditions were employed to set simple threshold levels for each one of the vibration parameters to distinguish between different conditions. More advanced signal processing and pattern recognition techniques can be employed instead. However, the focus is on offering a visual analytics view of the product, based on the data processing chain and not the exact signal and pattern analysis.

The visualisation application was developed in the *Processing* environment, an Open Source Development Environment for Interactive Visualisation. The application presents a range of options for interactive visualisation. The application can produce reports and visual analytics graphs for the raw signal, the measured parameters and the FFT of the raw vibration signal, as well as motor temperature (Fig. 6). The comparison of threshold values estimated from reference data and parameters extracted from subsequent observations is passed to the visualization layer of the application. This offers a 3D

model of the test rig highlighting visual features by colours, conveying contextual meaning. For example, sensor locations are marked in blue colour. The diagnosis outcome is communicated by superimposing fault conditions features on the 3D CAD product representation, wherein mechanical components are highlighted in red to indicate faulty condition. Visual features such as the above can be seen in an example screen captured from the visualisation application (Fig. 7).

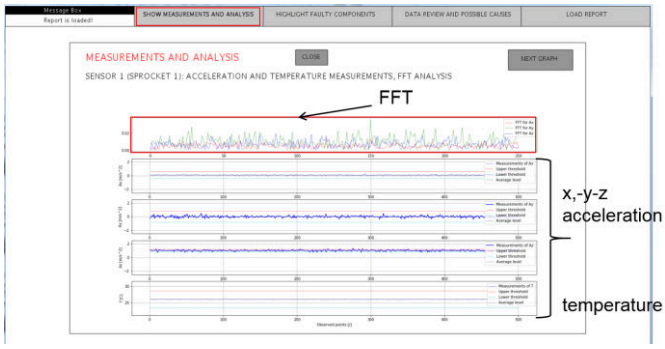

Fig. 6. Visual analytics example from the demo application

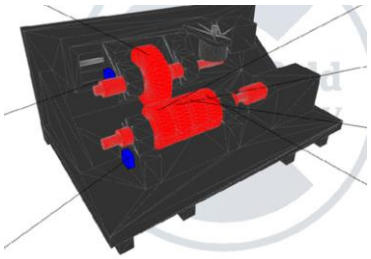

Fig. 7. Measurement locations and diagnosed failure modes

Typical monitoring systems already convey measurement data and faults to users. However, blending visual features in 3D product representations further aids a user to interact with product relevant data in a way relevant to non-monitoring contexts, such as when reviewing historical data and FMECA knowledge (Pistofidis et al., 2016). Maintenance linked knowledge can be actionable when shared in a contextually relevant way. In this example, a user handling FMECA knowledge is supported with visual features to understand the context of timelines of knowledge-rich events, and is thereby better aided to perform a FMECA revision cycle (Pistofidis et al., 2016). Thus, a design-stage tool, namely FMECA, is looked upon together with MOL data and disseminated in visually relevant ways, contributing to upper layer context management, ie context dissemination (Perera et al., 2016).

5. CONCLUSION AND FURTHER WORK

PLM tools now provide advanced features that enable teams to share context-specific product views and manage different lifecycle phase data and activities. The early vision of closed loop PLM was to integrate data from different lifecycle phases. Such a vision was greatly advanced by the introduction of the smart product concept, able to communicate its identity and status. The deeper penetration of IoT technologies and the emergence of IoT- enabled products has made the smart product concept a reality. Product data exchanges enable users to become more proactive actors within the PLM process. This paper introduced a conceptual approach and a pilot implementation of how this can be achieved by superimposing MOL relevant product information to BOL product views, such as a 3D product CAD model. Coupled with a range of visual analytics features, linked maintenance data and knowledge become visual features of a product design representation, assisting the understanding of MOL concepts, such as occurrence of failure modes. The approach can be useful when dealing with product data streams as a natural visual analytics add-in for closed loop PLM.

In the present work the diagnostic outcomes are produced as a result of simplistic processing. However, any other approach can be integrated, including streaming analytics (Katsouros *et al.*, 2015) or off-line diagnostics (Emmanouilidis, Jantunen and MacIntyre, 2006). Furthermore, such features can be linked with an appropriately populated Failure Modes, Effects, and Criticality Analysis (FMECA) knowledge tool, as for example presented in (Pistofidis *et al.*, 2016). Another natural extension would be to project digital product views, blending maintenance related with 3D product views on a virtual or augmented reality application (VR or AR). Visual analytics can also become a natural extension and context dissemination mechanisms of simulated, rather than acquired data. While simulation is already part of the design – stage product design toolset, the closure of information loops between MOL and BOL data can also be performed on simulated processes, enabling a better understanding of the functional performance of components and products before manufacturing and operating them, thus bringing together model and simulation based approaches with data driven ones. The overall approach can be integrated within a complete PLM process, which is targeted in our current project on IoT and Big Data in PLM.

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