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UNDERSTANDING THE APPLICATION OF DIGITAL TWIN TECHNOLOGY IN DIFFERENT FIELDS

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Abstract : A digital twin is a technology which represents real-life objects or devices virtually . It is similar to 3D renderings of computer-aided design (CAD) models. But the main difference between digital twins differ and simple 3D models is that, digital twin technology also combines the physical elements and the dynamics of how that object or device operates in the real world. In other words, we can see, almost in real time, precisely how an object or device responds throughout its lifecycle. Just as an asset moves in response to factors such as climate, ambient temperature, user idiosyncrasies and so on, so does its digital twin. Digital twins do this by combining data collected from sensors on the device, with knowledge related to the design, build, operation and servicing of the physical twin. Already, just from this data, we can have a rich, highly detailed picture of the asset. Intelligence, in the form of mathematics, physics, and machine learning and then building on data, has acted as a 'brain' of digital twin technology and performs things like model prediction, development and early warning systems happen. Multiple forms of digital transformation are imminent. Digital Twins represent one concept. It grows because it can give real visibility. The rapid spread of digital twin is facing obstacles due to the lack of semantic interaction between structures, levels and ontologies. The technology required for automatic detection is lacking. The continuity of the forum depends on the combination of information technology, operational and communication technology with protocol-agnostic. Making sense of the data, ability to curate data and perform data analytics at the edge is key to value. Delivering engines to the edge are crucial for analytics at the edge when latency is critical. The combination of these and other factors may chart the future path of Digital Twins. The amount of unknown unknowns and the known unknowns in this process makes it imperative to create global infrastructures and organize groups to pursue infrastructure development blocks and new ideas through research.

IndexTerms - Digital Twin, Digital Twin Data, DTD

INTRODUCTION

With the rapid development of new information technologies the digital economy continues to flourish on a global scale. Especially in the field of intelligent production, Digital Twin is widely used in store management and management, rapid production line production, product life cycle management, intelligent design, flexible planning, robotic efficiency, product quality assurance, machine tool maintenance and human robot interaction. The practical use of digital twins involves a collection of critical permitting technologies, related to the construction and validation of visual models, the construction and management of intelligent services, real-time sensitivity and material control, cyber-physical interaction and integration, many- modal data integration and integration, and so on. Since data is important in facilitate all of these technologies, it can be argued that the success of digital twin lies in the availability of high quality data source.Pre-phase data acquisition is usually done manually, with low efficiency and high cost. Since the data collected is small in value and poor in real-time performance, it can only reflect the characteristics of the visible business for a limited time with unavoidable delays. Benefiting from the exposure of new information technologies in recent years, large amounts of data can be collected by sensors, IoT devices, mobile devices, and wearable devices in real time and processed using integrated computer infrastructure. As a result, it is possible to obtain a complete data record and perform timely analysis throughout the virtual business life cycle. On the other hand, the growth of DT-related research and use prioritizes new data needs. While the concept of digital twins has been around since 2002, it is only with Internet of Things that we have called for it. Digital twin is a visual model of a process, product or service. This integration of the physical and virtual worlds allows data analysis and monitoring systems to solve problems before they occur, prevent downtime, develop new opportunities and even plan for the future through simulations. A digital twin can also be defined as a digital representation of a process or current and historical state of a physical object. This visual representation provides the capabilities and features of how an IoT device lives and works. Continuous reading and updates enable digital twins to provide real-time location, status and physical asset status. This integration of the real world with the digital world enables organizations to monitor systems, develop systems, and anticipate problems before they occur. Digital twins are created using digital twin technology.

Composition of Digital Twin Data: Digital Twin Data refers to a wide range of data that is related to digital twins. It equally focuses on virtual data collected and virtual-generated data and tends to make data from two spaces edited and added to each other by combining data, in order to achieve more accurate and complete information of Digital Twin-related applications. It can be divided into six categories, namely, business-related data, visual model-related data, service-related data, integration data, connection data and domain data. Physical business refers to an existing entity in the real world with certain functions, behaviors, and structures. According to ISO 23247-3, business-related data can be grouped into two categories: one is static information related to the physical entity and the other reflects the dynamic situations. This data can help to represent the business in a digital way. Visual models produce and define what is visible in the digital space with respect to various features, such as geometric structures, visual parameters, flexible behavior, operating and maintenance rules, and more. forward. Visual model related data includes model parameters and simulation data. Visual model related data is naturally associated with business-related data, as visual models are built on the visual business. Digital twin services can be categorized by application services and active services. App services are provided, based on business-related portable data and virtual model data, to directly address issues in a particular application environment, such as device prediction, resource planning, and product quality assurance. Therefore, service-related data primarily contains performance data, configuration data, and quality data. On the other hand, functional resources are provided to support the normal operation of the digital twin by recognizing relevant functions such as model management, data processing, data connection, etc. The related data therefore includes model configuration data, algorithm configuration data and service encapsulation data and so on.

LITERATURE SURVEY.

The following section identifies the related function of IoT / IIoT and data analysis with a focus on Digital Twins publication, discussing list publishing and identifying spaces in the field. This insight from the studies will help other researchers, enabling them to find gaps within the study and will allow movement to the broader definition of Digital Twin.

Modern Review Method

The first part of this section is a review of the relevant literature sections, following the method used by Kritzinger et al,[5] to produce a review for selected publication categories.The key features of the review draw on the three levels of Digital twin integration, as described in Section II, paragraph B of this paper and Kritzinger et al. [5]./The methodology used in this paper is based on the work performed by Kritzinger et al. [5], which includes the distribution of forty-three papers related to the topic Digital Digital, published between 2001 and 2017. Papers found on book search engines, such as Google Scholar. In a study of this paper, the authors used Google Scholar and specific search targeting ACM, IEEE and Science Direct. In the study found there were 177 papers to look at from 2015 to date (31st December 2019), with only 42, prior to 2017. Search terms include a variety of Digital Twin (Digital-Twin, Digital Twins). Along with the term Digital Twin, the search includes adding words related to a wide range of research areas (Industrial Digital Twin, Healthcare Digital Twin, Smart Cities Digital Twin).

Analysis of The Paper Not Revised

The papers in the review section, discuss the paper in detail, highlighting any ideas and case studies that have been done. The categories do not end there but will include, the main areas of paper collected related to health care, smart cities and manufacturing. The layout of the areas indicated reflects the current level of research in terms of the number of papers found. With health care, the number of papers received is limited, but the potential health benefits Digital twins can have in the health care industry are common [6]. Next is a clever downtown area with a small number of papers found. Much research falls within the production environment.

1) Health care

A factor to be taken from a few descriptions of the Digital Twin concepts as described by He [5], is the“digital duplication" of the physical . El Saddik has redefined this by incorporating Digital Twin reproduction into biological and inanimate organizations . Introducing the potential use of Digital Twin for the healthcare sector shows that it is not limited to production.From a health perspective, Digital Twin technology, combined with AI algorithms, can be used to detect the potential effects of certain changes in a person's lifestyle, recommending specific changes from AI and Digital Twin analysis. This use emphasizes the full integration of data from both Real Twin (Man) and Digital Twin (Replica). Giving a person the ability to see the effects of their actions on physical twins while showing the effect that other lifestyle changes can have on them.

2) Wise Cities

This section focuses on current research involving smart cities with respect to Digital twins. Studies in recent years have seen significant urban growth combined with the rise of IoT and data analysis . Mohammadi et al. quote this as one of the motives for their work and identify various conditions for spatiotemporal flexibility, emphasizing that these need to be understood in order to maintain growth. The concept they present does this by using Digital Twin and real-time headset, which allows them to monitor flexibility while making predictions with real-time statistics.

METHODOLOGY

The life of digital twins begins with applied mathematical or data science experts who study the physical and operational data of a material or system to develop a virtual mathematical model. This allows the digital version to simulate and replicate what is happening with the real version in real time, creating opportunities to collect performance data and any potential problems. Digital twins can be as complex or simple as we need, a variety of data that determine whether the model accurately mimics the real world version. it can also serve as a model for itself which is possible with a portable version.

Comprehensive Data Gathering

Complete data is required to improve the accuracy, efficiency, and flexibility of DT-based services (e.g., performance assumptions, process improvements, and quality assurance). Comprehensive data refers to a broad data system that includes, for example, your data for both normal and uncommon status, your data for both normal and uncommon event, your data for both specific and uncertain conditions, and so on. DT applications built on incomprehensible data suffer from a variety of challenges. On the other hand, some of the existing work focuses on data collected in the physical world, where, it is difficult to include low probability data (e.g., failure data and overstatement data) as well as non-directly measurable data (e.g., conversion data, pressure distribution, and air flow) [1]. On the other hand, some work focuses primarily on data collected from visual models, where, it is difficult to accurately replicate data on disruption caused by sudden disruption and time-varying data and high uncertainty[2]. A successful DT solution should be enabled with full details obtained from both the physical and the natural world.

Real-Time Data Interaction

Real-time data interaction is required to enable integrated tasks. First, real-time data from a virtual business can be used to update visual model parameters, while simulation data from virtual models is returned to the virtual business to align its behavior with the simulation system. Second, data from DT-based services should be linked to the mobile business for timely diagnosis, adjustment, and control, while real-time data from the mobile business can be used to update services and adapt to changing physical and changing realities. . Third, as service availability must be verified prior to use, real-time simulation results for visual models should be communicated with service providers to indicate shortcomings, while service data may be used to measure visual models and improve their accuracy.

Knowledge Mining

In order to build intelligent visual models that can reflect the methods and rules of a viable business, it is necessary to obtain background information on raw data mining. Deep digging of big data (e.g., visual business data, virtual model data, and information system data) into new information remains a challenge. On the other hand, not all data is equally useful in extracting information and information, in particular, about non-essential data, abnormal data, and non-essential data. On the other hand, it is difficult to fully dig deep into the hidden information behind the data.

Low data universality is a major barrier to DT applications. It is difficult to transfer DT to all different application scenarios, including different requirements and barriers to data acquisition. The difficulty of exchanging and separating data is affected by the various components of a particular application environment, such as various physical objects (e.g., robot, machine tool, and autonomous vehicle), data links and communication protocols. Against different application environments (e.g., design, production, and storage), it is difficult to achieve smooth data integration and sharing due to different data formats. To address these issues, it is necessary to integrate the data conversion to the maximum data level.

Data Fusion

Since DT-related data comes from many sources (e.g., business entity, virtual model, and service), there is data noise, inconsistencies, and conflicts. In data collected in the visual business, various factors such as sensory dysfunction, environmental variability, and human impairment may affect information entropy (high value indicates high data uncertainty). In data mimicked by non-virtual models, the deviation from the material due to unsatisfactory model performance can reduce data reliability. In addition, no data collected or validated data is sufficient to obtain world views. Therefore data integration is required, by which, data obtained from various sources is synthesized. It will bring many benefits, such as reducing sensory data entropy (i.e. reducing data uncertainty), reducing root mean squared error (RMSE) between fixed data and limited data (i.e., improving data accuracy), and improving data correlation with specific target information. , such as product quality, service life remaining of the critical component, and healthy mechanical condition (i.e. increasing the amount of information related to the target index). In doing so, the data can be verified, edited, and added to each other, resulting in the release of more accurate and consistent information.

RESULT ANALYSIS

Digital Model

The Digital Model is the digital representation of an existing object or a structured visual object that does not use any kind of automatic data exchange between object and digital object. Digital representation may include more or an incomplete description of a tangible object. These models may be inclusive, but not limited to imitation structured industrial models, new mathematical models products, and any other models of material, makes do not use any type of automatic data integration. Digital data for existing systems are no longer in use development of such models, but all data exchanges are done internally hand method. A change in the state of the physical object does not direct effect on the digital object and vice versa.

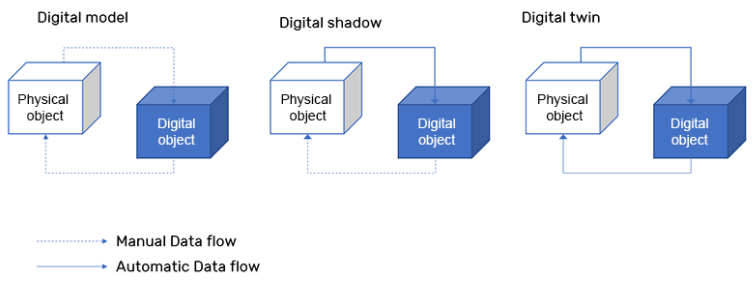

Figure 1: Data flow in three models

Key Enabling Technique

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Due to the different nature and different levels of integration of Digital Twin concepts, a set of technologies required to implementation varies greatly. Commonly considered technology include, but are not limited to imitation methods (e.g. Unique Event Simulation, Continuous Simulation, etc.),communication systems (e.g. OPC-UA, MQTT, etc.) and another technology commonly described as Industry 4.0 core technology (Internet of Things, Cloud Computing, Large Data, etc.). Therefore, the key to allowing technology, mentioned in the scrolls, they will be seen.

Implementation of Complimentary Principle

The DTD compliant policy complies with the requirement for complete data collection. Emphasizes simultaneous collection of data from virtual and virtual worlds, adding to each other and creating successive shortcomings. On the other hand, business-related data can actually reflect the dynamics of the physical reality, including uncertainty, confusion, and complexity, which is difficult to imitate. On the other hand, virtual models can generate data for a wide range of unusual events, non-standard data, and multi-physics integration simulations at low cost, which can be collected directly from the world. According to the corresponding policy, in terms of data collection, data from virtual and virtual worlds must be collected simultaneously to ensure data alignment. Real-time interaction is done with timely transmission and adjustment of connection data based on the principle of compliance. In accordance with the established principle, with regard to data storage, data with different formats, interaction links and protocols should be converted into standard ones. According to the organization's policy, various relationships between the various components of DT should be excluded to support ongoing mining. Based on the principle of integration, aggregation data is generated by combining the same data with the corresponding data for the same adjustment and addition. The principle of knowledge growth is followed to translate continuous data emergence.

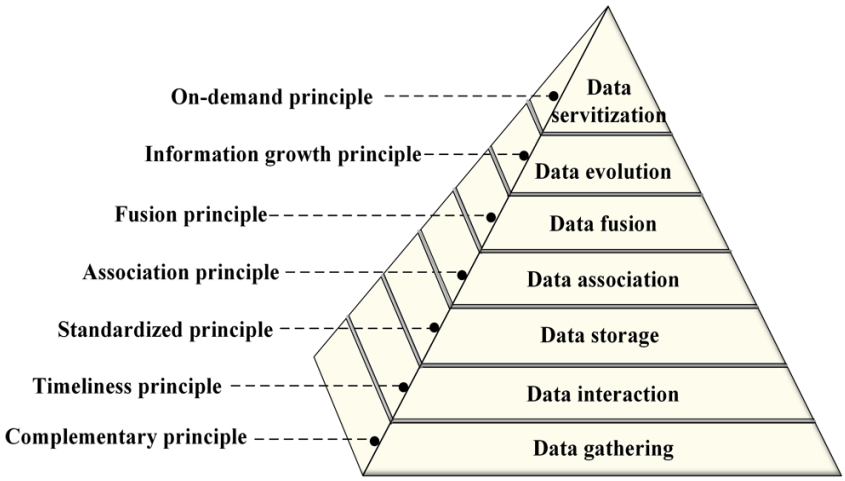

Figure 2: Digital Twin Data Methodology

Digital Twin Data Interaction

Communication data between any two components of the DTD supports real-time interaction. First, it is necessary to select the appropriate data to support the message transmission between any pair of two components. In the interest of data transfer, data is also processed by filtering algorithms, size reduction algorithms, and compliance analysis algorithms, which are intended to remove data noise and reuse. During the transfer, the compatibility of the contact data can be checked by calculating the data ranges. To better illustrate the interaction, take the as an example. During curing, the distribution of mold temperature within the autoclave is an important indicator of quality, as it significantly affects the degree of flexibility of the composite components[3]. To monitor the quality of the part, the actual temperature of the mold is collected by thermocouples. Although, a visual model can also be developed to mimic the distribution of mold temperature using CFD simulations. The data interaction between the material and the visual model is used to ensure that the actual treatment is performed as simulation. In this case, a major factor indicating the distribution of mold temperature, i.e. the difference between high and low temperatures in the surface area of the mold, can be selected as the connection data, leaving some unwanted or unimportant features. Then the collected and modified mold temperature differences can be exchanged and compared. If their deviation remains within the predefined limit, the expected

combination quality will be achieved. Otherwise, disruptive factors that cause conflict need to be identified, such as the uneven air flow in the autoclave, the deteriorating installation of the autoclave wall, and the rapid change in treatment conditions. These features should be removed by adjusting the visual autoclave parameters.

CONCLUSION

This paper provides the theoretical foundations of DTD, essential for the development and implementation of DT, to support additional DT researchers to incorporate DTD into their DT development program. This paper focuses on DTD that can be separated by business-related data, visual model-related data, service-related data, domain information, integration data, and connection data.The advent of DT prioritises some new data requirements regarding data collection, collaboration, space, mining, integration, duplication improvement, and usage where needed.Starting with these needs, seven basic principles are proposed to support the DTD organization and analysis.

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