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Visualization and visual analysis of multimedia data in manufacturing: A survey

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A B S T R A C T

With the development of production technology and social needs, sectors of manufacturing are constantly improving. The use of sensors and computers has made it increasingly convenient to collect multimedia data in manufacturing. Targeted, rapid, and detailed analysis based on the type of multimedia data can make timely decisions at different stages of the entire manufacturing process. Visualization and visual analytics are frequently adopted in multimedia data analysis of manufacturing because of their powerful ability to understand, present, and analyze data intuitively and interactively. In this paper, we present a literature review of visualization and visual analytics specifically for manufacturing multimedia data. We classify existing research according to visualization techniques, interaction analysis methods, and application areas. We discuss the differences when visualization and visual analytics are applied to different types of multimedia data in the context of particular examples of manufacturing research projects. Finally, we summarize the existing challenges and prospective research directions.

1. Introduction

In recent years, the manufacturing industry plays an increasingly important role in social and economic development. The core of Industry 4.0 is smart production technologies and models. It aims to connect products, machines, resources and people through IoT and internet of services (IoS), promote data sharing among all aspects, and realize the digitalization of the whole product life cycle and the whole manufacturing process (Cardoso et al., 2010; Gubbi et al., 2013). After investigating and analyzing country-led policies and proposed technology roadmaps, we can learn about five key technologies related to smart manufacturing, which are cyber–physical systems (CPS), cloud manufacturing, big data analytics, internet of things (IoT), and smart sensors (Gehlot et al., 2022; Kang et al., 2016). Besides, there are three application technologies, which are 3D printing, smart energy, and hologram. However, it is worth mentioning that these technologies do not analyze the data generated in the whole process of manufacturing.

The entire manufacturing process can be broadly divided into three main phases: *Design & Development*, *Production & Testing*, and *Sales & Service* (Zhou et al., 2019). Each of the three phases has tasks that generate different types of data. The tasks in *Design & Development* phase besides the design and development of product styles and functions also include the site planning of factories and stores. In *Production & Testing* phase, raw material distribution ordering , staff and equipment scheduling, product quality and production line monitoring and analysis are all hot directions of research. In *Sales & Service* phase, product promotion and advertising design (Guo et al., 2021), sales data and feedback analysis are also very important. The data generated in the above phase includes tabular, text, images, videos, and sensing signals. Multimedia data includes one or more major media data types. Multimedia data is used in this paper as a collective term for data generated by the entire manufacturing process.

Along with the use of sensors and computers, it is becoming easier to collect data of manufacturing. Consequently, the real-time nature of data itself and the correlation between data have been enhanced. Targeted, rapid, and detailed analysis based on the type of multimedia data can make timely decisions at different stages of the entire manufacturing process (Marconi et al., 2021; Yao et al., 2019). It is also the internal motivation for research on multimedia data in manufacturing. Visualization and visual analytics is a comprehensive subject that is closely related to many research areas such as graphics, data mining, and human–computer interaction. Visualization and visual analytics technologies have multiple ways to convert massive amounts of information into knowledge and reasoning intuitively and efficiently. Because of their intuitiveness and effectiveness, they are frequently used in the analysis of multimedia data in manufacturing.

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In this paper, we systematically review research work related to the visualization and visual analysis of multimedia data in manufacturing. We introduce a methodology for paper collection and review, and propose a novel taxonomy based on multimedia data types. Then, we summarize the collected papers in three dimensions: visualization techniques, interaction analysis methods, and application areas.[1] Finally, we conclude with a discussion of existing work and provide suggestions for future work.

2. Related surveys

In this section, we review surveys related to manufacturing. As the manufacturing industry has a wide range of categories and complex processes, there are many research directions and objects for the manufacturing industry. These high-quality surveys cover data, technologies, and concepts in manufacturing (Baboli, 2021; Chhikara, 2022; Cui et al., 2020; Park et al., 2020; Qu et al., 2019). Next, we discuss the available surveys from both micro and macro perspectives.

• **Particular data or technologies in manufacturing**. ① Data processing techniques. For complex high-dimensional data in Industry 4.0, Chhikara (2022) compared different dimensionality reduction techniques from two tasks, feature extraction and feature selection, and gave insights into their applicability. ② Visualization of particular industries. Taking automotive manufacturing as an example, to better understand different types of data flow, Stevens et al. Schlereth and Birklein (2007) introduce four categories of visualization applications and illustrate the role of visualization in automotive manufacturing. ③ Particular visualization techniques. Both augmented reality (AR) and virtual reality (VR) have a wide range of promising applications of manufacturing data visualization. Bruno et al. (2006) presented the application of AR for industrial engineering data visualization, while de Souza Cardoso et al. (2020) assessed the applicability of AR and its impacts on real industrial processes. Berg and Vance (2017) investigated the application of VR in design and production of products.

• **Concepts & definitions, as well as experience summaries**. ① Concepts & definitions. The concepts and definitions involved in manufacturing are very complicated. In addition to the ones that provide an overview of the development, definition, goals, and various needs and components of smart manufacturing (Qu, 2020), others propose new evaluation metrics (Baboli, 2021). ② Experience summaries. The summary of experience can provide professional guidance for follow-up work. Cui et al. (2020) summarized the drivers of big data applications in manufacturing, while Yin et al. (2014) made a careful investigation around the basic data-driven approaches to industrial process inspection. In addition, Park et al. (2020) proposed a detailed operational procedure for digital twin. Using examples, David et al. Font Vivanco et al. (2019) explored the value of interactive visualization and highlighted the challenges that industrial engineering community must face in the interactive visualization process, including technical and knowledge limitations, user interaction limitations, and implementation strategies.

The above high-quality research works not only provide an adequate theoretical foundation but also inspire our formalization of the design space. Unlike existing work that summarizes techniques for particular visualization, visual analytics task, or manufacturing-related application, our work aims to provide a more comprehensive approach to visualization and visual analytics for multimedia data in manufacturing, and thus practitioners benefit from a wider range of research results.

[1] https://zjutvis.github.io/MMDM/

3. Methodology and taxonomy

3.1. Methodology

To clarify the scope of this survey, we articulate three terms used in our work: manufacturing, multimedia data, and visualization/visual analytics. First, it is important to note that manufacturing is the area we investigated. We focus on those manufacturing categories which have a high degree of computer technology and automation. E.g., computer manufacturing, automobile manufacturing, household electric appliance manufacturing, etc. Secondly, we analyze multimedia data from the whole process of manufacturing industry, including both structured and unstructured data. Finally, we are concerned with the visualization and visual analytics techniques used in these studies. We attempt to investigate visualization and visual analytics techniques of multimedia data in manufacturing to discover application areas of interest to the visualization research community, as well as visualization techniques and interactive analysis methods.

We searched for papers that have been published in visualization conferences or journals based on the following keywords: "manufacturing", "industrial", "smart manufacturing", "smart factory", "intelligent manufacturing", "manufacturing process", "industry 4.0". Visualization conferences or journals including but not limited to *IEEE VIS, EuroVis, PacificVis and IEEE TVCG.* We then searched for papers in industrial manufacturing-related conferences or journals based on the following keywords: "visualization", "visual analytics", "data analytics", "virtual reality or VR", "augmented reality or AR", "digital twin". Manufacturing-related conferences and journals including *IEEE TIE, Journal of Intelligent Manufacturing, Additive Manufacturing*, etc. Finally, we searched for papers in conferences or journals in human–computer interaction, artificial intelligence and data mining based on the following keywords: "industrial equipment + visualization", "industrial data + visualization", "industrial systems + visualization". Related conferences and journals include *ACM CHI, ACM TKDD, IEEE SMC,* etc. After that, three researchers, who are familiar with both visualization and multimedia data in manufacturing, further screened the collected papers. The selection criteria are: ❶ The papers were published in journals and conferences with high recognition; ❷ The content of the papers included both "visualization and visual analytics" and "manufacturing"; ❸ The visualization and visual analytics related technologies proposed in the paper can be applied in the manufacturing industry now or in the future. The statistics show that the papers collected were published between 2009 and 2022.

Moreover, our work attempts to explore visualization techniques, interactive analysis methods, and application areas of interest to the visualization research community in manufacturing, based on high-quality reviews.

3.2. Taxonomy

Inspired by the high-quality review mentioned in Section 2, we propose a novel taxonomy based on data types to summarize the visualization and visual analysis of multimedia data in manufacturing. We have added recently published works and discuss them in terms of visualization techniques, interactive analysis methods and application areas. We encode the different classification dimensions with different colors: for multimedia data types, for visualization techniques, for interactive analysis methods, and for application areas.

Multimedia data types. Multimedia data can be broadly classified into three main categories according to data types: *Signal sensing data* (SS), *Image & video data* (I&V), *Tabular & text* *data* (TT). Signal sensing data contains data collected by various sensors, including audio data by sound sensors, motion data by infrared optical motion sensors, and trajectory data by sensors in IoT. Some of the *Image & video data* are real data, some are generated by digital simulation, and others are related to AR and VR. Tabular & text data contains data stored in both tabular form and text form. There is a large amount of data as tabular forms, such as sales records, product parameters, production logs, etc. User complaints and suggestions, product descriptions, and maintenance record descriptions are stored in text form.

Visualization techniques. We classify visualization techniques applied to multimedia data in manufacturing as *sequence, graph, text, chart, glyph, and volume visualizations*. Sequence visualization illustrates the temporal information that the data has. Sequence visualization can identify anomalies in the data and explore patterns in the development. Researchers present time as a separate dimension, for example by specifying a coordinate axis to represent time. The corresponding visual representation can be timeline visualization and flow visualization. More detailed presentation of data attributes on each time scale, such as parallel coordinate systems, is also available. Graph visualization is a network structure comprising of points and edges. The network structure can be directed or undirected. Typical graph visualizations include node-link diagrams, trees, and Sankey diagrams. Graph visualization allows users to discover associations between data, such as hierarchical relationships, attribute associations, and codependencies (Burch et al., 2021; Zhao et al., 2021). Text visualization focuses on whether to introduce text data in visual analysis. In addition to word clouds, text visualization can be visually enhanced by highlighting and also paired with other visualization techniques to show more contextual content, such as flow visualization. Chart visualization mainly refers to the presentation with the help of traditional visualization elements. Typical chart visualizations are scatter, bar, line, heat and bubble charts, etc. Distinguished from chart visualization, glyph visualization refers to the targeted design on visualization elements to produce a new visual representation. Volume visualization can be described as the 3D rendering of objects. In manufacturing, objects can be imaged in 3D after being scanned by Computed Tomography (CT), or generate 3D digital simulations from image data. Besides, we categorize some VR-related and AR-related work into volume visualization.

Interactive analysis methods. We summarize the high-level interactive analysis methods (Yi et al., 2007) which are commonly used in manufacturing multimedia data visualization, including *Tracking & Monitoring* (TM), *Exploration & Navigation* (EN), *Knowledge Externalization* (KE), and *Refinement & Identification* (RI). *Tracking & Monitoring*: mark data of interest by clicking, hovering or brushing. *Exploration & Navigation*: review data by panning, zooming, drop-down or roll-up. *Knowledge Externalization*: collect, save and extract current visualizations by taking snapshots. *Refinement & Identification*: label data by known identities. Researchers and operators may use these four categories of interactive analysis methods to complete visualization and analysis tasks for manufacturing multimedia data.

Application areas. According to the actual production needs of the manufacturing industry, we classify the application areas of multimedia data visualization and visual analysis in manufacturing into four categories: *Design & Development* (DD), *Production & Testing* (PT), *Education & Training* (ET), and *Analysis & Feedback* (AF). *Design & Development*: appearance and function of products. *Production & Testing*: product production and function testing. *Education & Training*: staff competency training and knowledge science of manufacturing. *Analysis & Feedback*: analyzing the data and drawing conclusions to provide feedback to the other three application areas.

		SS	I&V	TT	Sequence	Graph	Text	Chart	Glyph	Volume	T&M	E&N	KE	R&I	IP	ET	DD	AF
Pantforder et al. [52]	2009		■							■		■	■			■		
Pretorius et al. [55]	2011		■			■		■			■	■	■	■			■	■
Meyer et al. [46]	2013			■	■		■	■			■	■		■				■
Basole et al. [5]	2014			■		■		■			■	■		■				■
Jo et al. [34]	2014			■	■			■			■	■	■					■
Sharif et al. [61]	2014			■		■	■	■				■		■				■
Fulda et al. [25]	2015			■	■		■	■	■		■	■	■	■				■
Amirkhanov et al. [1]	2016		■							■		■	■	■			■	■
Park et al. [54]	2016			■		■	■					■		■				■
Chen et al. [12]	2017			■	■			■	■		■	■	■	■				■
Dutta et al. [19]	2017	■			■			■		■	■	■	■	■			■	■
Gkorou et al. [27]	2017		■					■			■	■		■	■			■
Yu et al. [76]	2017			■				■			■	■		■				■
Zhao et al. [78]	2017	■			■			■			■	■	■		■		■	■
Blumenschein et al. [8]	2018			■				■			■	■		■				■
Herr et al. [32]	2018			■	■			■			■	■	■	■				■
Wang et al. [68]	2018			■			■	■	■			■	■	■			■	
Cirp et al. [15]	2019		■							■		■	■				■	■
Mei et al. [45]	2019			■				■			■	■	■	■				■
Moreland et al. [47]	2019		■							■			■			■		
Sun et al. [62]	2019			■	■			■	■		■	■	■	■	■			■
Wang et al. [69]	2019			■	■		■	■	■		■	■	■				■	
Zappulla et al. [77]	2019	■								■			■		■			■
Zhou et al. [80]	2019	■			■			■	■		■	■			■			■
Cibulski et al. [14]	2020	■			■			■	■		■	■	■	■	■		■	■
Murithi et al. [48]	2020		■							■		■	■		■			■
Oppermann et al. [51]	2020			■			■	■			■	■	■	■				■
Suschnigg et al. [63]	2020	■			■			■			■	■						■
Suzuki et al. [64]	2020	■								■			■		■			■
Tao et al. [66]	2020		■							■		■	■				■	■
Eirich et al. [20]	2021	■			■			■	■		■	■	■	■	■		■	■
Gove et al. [28]	2021			■	■			■	■		■	■	■	■				■
Liu et al. [41]	2021			■				■			■	■	■				■	
Narechania et al. [49]	2021	■				■	■	■			■	■	■	■			■	■
North et al. [50]	2021		■				■	■			■	■	■		■			■
Satkowski et al. [59]	2021		■				■	■			■	■	■		■			■
Tang et al. [65]	2021			■	■			■			■	■	■	■	■			■
Yoo et al. [75]	2021		■							■	■	■	■	■			■	■
Becher et al. [6]	2022		■		■		■	■			■	■	■		■			■
Klacansky et al. [37]	2022		■							■		■	■				■	■
Qian et al. [56]	2022			■	■	■		■			■	■	■	■				■
Wang et al. [67]	2022	■				■		■			■	■	■	■			■	■

Fig. 1. We categorize the published papers based on manufacturing multimedia data types, visualization techniques, interactive analysis methods, and application areas. We encode the different classification dimensions with different colors: for multimedia data types, for visualization techniques, for interactive analysis methods, and for application areas.

From Fig. 1 and Fig. 2, we can get the following conclusions: ❶ Among the three multimedia data types, *Tabular & text data* has the most papers; ❷ Among the visualization techniques, Chart has the most papers; ❸ The number of papers in each subcategory of interactive analysis methods is roughly the same; ❹ Among the application areas, *Analysis & Feedback* has the most papers.

4. Signal sensing data

In this section, we will discuss for signal sensing data in manufacturing processes. A wide variety of sensors are used in manufacturing production to collect data from mechanical equipment, manufacturing lines, and manufactured products, which include temperature, humidity, pressure, flow, speed, position.

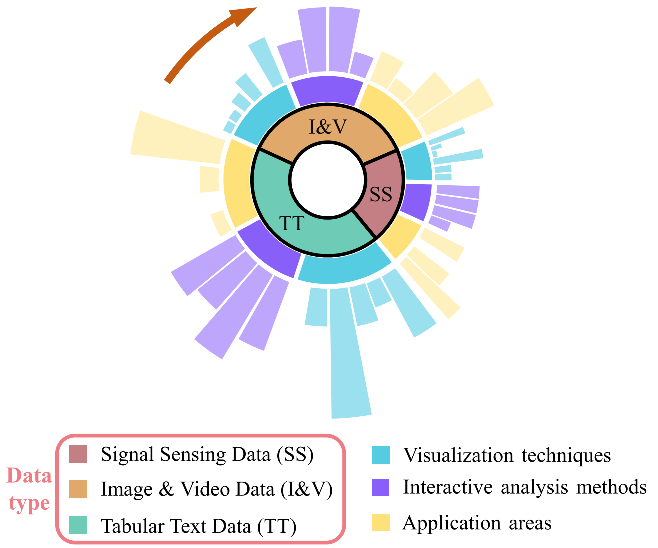

Fig. 2. We divided the collected papers into three categories based on multimedia data types: *Signal sensing data*, *Image & video data*, and *Tabular & text data*. Then, extract involved visualization techniques: *Sequence, Graph, Text, Chart, Glyph and Volume*. Next, generalize covered interaction analysis methods: *Tracking & Monitoring*, *Exploration & Navigation*, *Knowledge Externalization*, and *Refinement & Identification*. Finally, summarize application areas: *Design & Development*, *Production & Testing*, *Education & Training*, and *Analysis & Feedback*. The above subcategories are all sorted in the direction shown by the arrows. The height of fan chart represents the number of papers in each subcategory.

4.1. Visualization techniques

Sequence visualization is frequently used in sensing signal data presentation. Engine speed, engine torque, temperature, pressure and exhaust gas measurement data are time-sensitive. These kinds of data are often recorded with sensors. A flexible and expandable visual analysis method for engine anomaly detection was proposed by Suschnigg et al. (2020). To investigate the key factors of automotive engine durability, Zhao et al. (2019) proposed a visual analysis method to understand large-scale long-term durability test data. In addition to machine status, the analysis of worker's motions is also based on chronological order. Kagaya et al. (2017) developed a technique using a motion sensor to record time-series 3D coordinate data of worker's motions during preventative maintenance in order to extract important indications of high-quality maintenance work.

Chart visualization is commonly employed to analyze different signal sensing data and complete visual analysis tasks. Real-time analysis of sensing data for production monitoring and industrial design through histogram (Eirich et al., 2021; Zhou et al., 2018), scatter diagram (Cibulski et al., 2020; Eirich et al., 2021) and parallel coordinate (Cibulski et al., 2020). Zhou et al. (2018) designed a visual analysis system which combines information rich glyph and sequence diagram to achieve the routine monitoring and troubleshooting of the complex key manufacturing facility *Roller Hearth Kiln* (RHK). *IRVINE* (Eirich et al., 2021) used acoustic data to detect and understand previously unknown errors in the manufacturing of electrical engines. Analyze offline sensing data using visualizations such as node-link graph (Wang et al., 2022), network and cluster (Narechania et al., 2020). Via network and cluster exploration technologies, *SafetyLens* (Narechania et al., 2020), as a visual data analysis tool, assisted engineers analyze automotive functional safety data sets (see Fig. 3).

Volume visualization is often utilized to design products and perform simulations. Suzuki et al. (2020) chose volume visualization to display a load path in the composite material structure and aligned fiber with the direction of load path. l Zappulla et al. (2019) introduced a methodology for the processing of high-density data from temperature sensors and used 3D visualization of thermal fluid flow fields in mold region during continuous steel-slab casting. Huettenberger and Garth (2015) used the data produced by optical measurements to visualize the areas of systematic errors on auto parts in order to achieve automatic detection. Dutta et al. (2016) developed the tech of visualization of GMM based data using surface renderings and uncertain isocontours to detect the early signs of transonic jet engine stall.

4.2. Interactive analysis methods

Interactive analysis methods assist researchers in uncovering hidden patterns (Narechania et al., 2020) and worthwhile information (Eirich et al., 2021) in signal sensing data. The prototype systems (Eirich et al., 2021; Zhao et al., 2019; Zhou et al., 2018) designed by researchers provide a set of operations to assist users achieve interactive data exploration. *Tracking & Monitoring* assist users in carrying out fluent data exploration. Zhao et al. (2019) and Zhou et al. (2018) provided interaction in many views and panels. When users move or click the mouse in each view, detailed information will be displayed. In addition, they provided a multiple-view display mode for further observation and analysis. *Exploration & Navigation* provide detail-on-demand and views update for users. *PAVED* (Cibulski et al., 2020) offered a selection on motor parameter subset performance constraints and preferences by a transformation of the mouse cursor. *Knowledge Externalization* and *Refinement & Identification* are commonly utilized in anomaly detection and situational monitoring. Eirich et al. (2021) combines interactive clustering and data labeling techniques, allowing users to analyze clusters of engines with similar signatures. Analyzing signatures of engines acoustic data to detect and understand previously unknown errors.

4.3. Application areas

Signal sensing data come from numerous sources and are mainly applied to *Design & Development*, *Production & Testing*, and *Analysis & Feedback*. In *Design & Development*, these works (Huettenberger and Garth, 2015; Suzuki et al., 2020; Zappulla et al., 2019) use optical, pressure and temperature sensor data to visualize manufacturing materials and products. Other works are devoted to the analysis of multi-sensor data through visualization techniques for the study of durability (Zhao et al., 2019), safety (Narechania et al., 2020), and abnormal states (Eirich et al., 2021) of products. In *Production & Testing*, several visual analytics systems are designed for industrial production situational monitoring (Zhou et al., 2018), production quality control (Huettenberger and Garth, 2015) and manufacturing product inspection (Eirich et al., 2021). In *Analysis & Feedback*, most of the research work have the analytical feedback component, e.g., the analysis of parameter sets for the improvement of electric motor design by means of human–computer interaction and expert collaboration (Cibulski et al., 2020) (see Fig. 4).

4.4. Discussion

Due to the diversity and complexity of signal data, generic visual analytics solutions and frameworks are difficult to apply to research and development and production processes in the manufacturing industry. Current visualization researches work on the development of a specific manufacturing process or product, such as SafetyLens (Narechania et al., 2020), *PAVED* (Cibulski et al.,

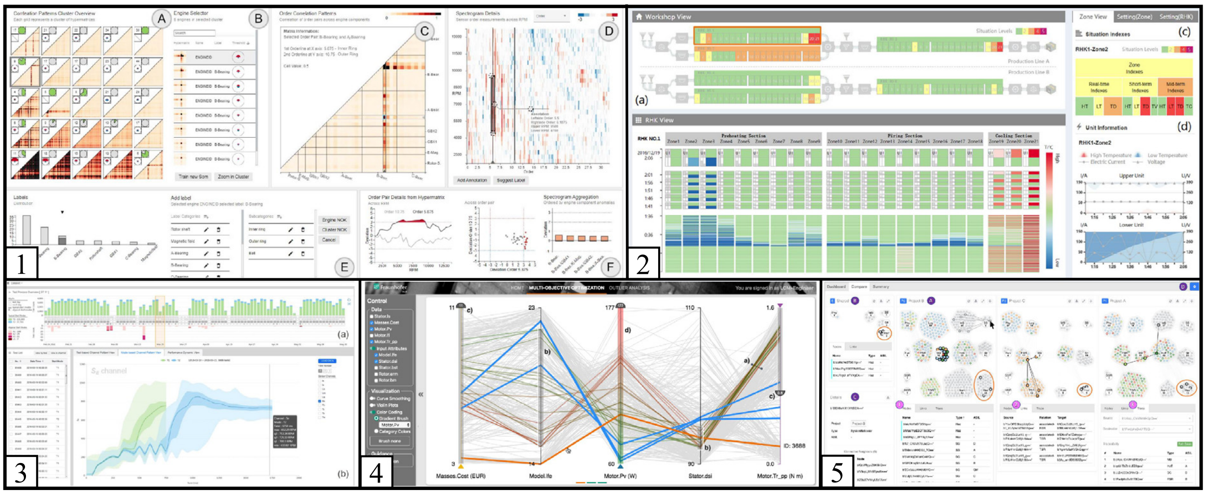

Fig. 3. Visualization and analysis of signal sensing data. (1) Visualizing and analyzing correlation patterns of electrical engines (Eirich et al., 2021). (2) Situation awareness and visual analytics for the routine monitoring and troubleshooting of Roller Hearth Kiln (Zhou et al., 2018). (3) Visual analysis for understanding the durability of automotive products (Zhao et al., 2019). (4) Pareto front visualization of engineering design (Cibulski et al., 2020). (5) Visual data analysis of functional safety of vehicles (Narechania et al., 2020).

2020), *IRVINE* (Eirich et al., 2021), and so on. These visual analytics systems do help to solve some challenges in actual industrial manufacturing and design development. However, these efforts commonly require professional engineers to work together, and the excessive specialization makes the visualization solutions no longer universal. In addition, when it comes to multi-sensor data analysis, it is worthwhile to investigate how making good use of these diversified data to discover new patterns.

5. Image & video data

In this section, we will discuss for image and video data in manufacturing processes. The application of photographic camera equipments in the manufacturing industry generates a large amount of image and video data, which are used to monitor the operation of equipment in factories and to check the quality of products. Video data, when extracted by frame, can also be considered as image data. Therefore, the methods for handling both kinds of data can be common to some extent. Previously, the analysis of images and videos required human intervention. It was labor-intensive and the balance between efficiency and accuracy could not be maintained. With the enhancement of computer computing power and GPU performance, the analysis and research of image and video data have become more convenient and become an emerging research direction in manufacturing multimedia data. At the same time, the rise of artificial intelligence and machine learning in recent years has made it possible to process image and video data efficiently and accurately. And the development of VR and AR has expanded the analysis of data from two-dimensional to three-dimensional, while adding new visual displays and interactive analysis methods (Yoo and Kang, 2021).

5.1. Visualization techniques

Graph visualization is often used in relevant researches for the analysis of image and video data in order to facilitate the classification and the presentation of parameter relationships. Pretorius et al. (2011) proposed a paradigm shift for optimizing parameters based on parameter sampling and interactive visual exploration. They designed a prototype called *Paramorama*, where the relationship between the input parameters and the corresponding

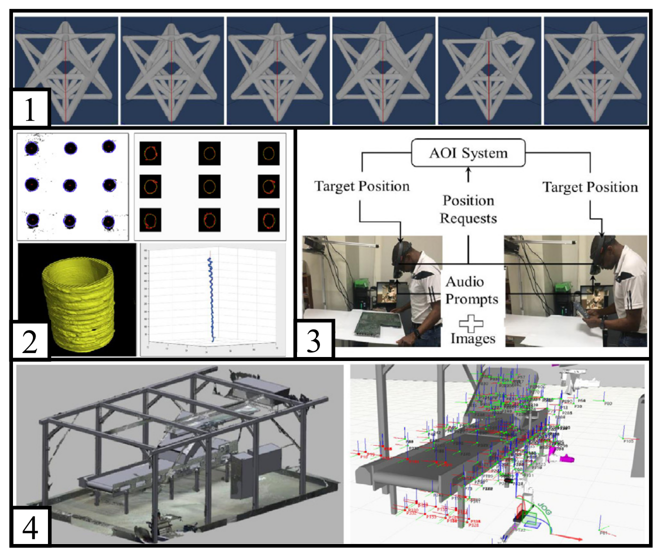

Fig. 4. Research on applications of *Image & video data* for defect detection.(1) Volume visualization of physical structure of additively manufactured parts, including one normal case (far left) and five abnormal cases (Klacansky et al., 2022). (2) Detection of machining accuracy of PCB holes (Tao et al., 2020). (3) Markerless cooperative AR-based intelligent manufacturing review system (Murithi and Lin, 2020). (4) Checking equipments' installation with 3D scanning (Cirp et al., 2019).

outputs was presented using a tree (directed acyclic graph). Additional constraints were added to the node-link graph in *CommunityDiff* (Datta and Adar, 2018) so that nodes classified as the same community are restricted to the same rectangle, while maintaining connections between nodes. Node-link graphs are also used in *Locomotion Vault* (Luca and Seif, 2021), a visualization tool and a database of over 100 techniques that were proposed by researchers and practitioners in the academia and industry, to represent the similarity between different technologies.

Chart visualization is one of the common visualization techniques used in image and video data analysis. In the work of (Gkorou et al., 2017), the most relevant factors for monitoring and diagnosing high volume semiconductor manufacturing were visualized and ranked, where scatter plot, heatmap and boxplot

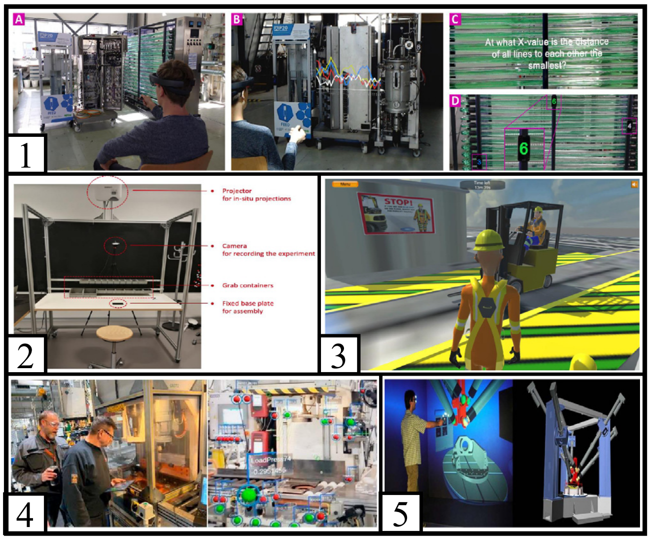

Fig. 5. AR and VR in manufacturing. (1) Assisted industrial assembly training with a projection-based AR system (Satkowski and Dachselt, 2021). (2) VR applications in manufacturing systems (Büttner et al., 2020). (3) Interactive simulator for steel industry safety training (Moreland et al., 2019). (4) AR that uses the real factory environment as a background to display equipment information (North et al., 2021). (5) Final demonstration and use of the industrial internet of things (IIoT) based AR for factory data collection and visualization by Volvo technicians (Hamid et al., 2014).

were utilized. Bar chart was used in *Locomotion Vault* to show the number of technologies in each year.

Volume visualization of products and industrial equipments can be performed by means of 3D scanning or digital simulation techniques. Amirkhanov et al. (2016) used 4DCT data for numerical modeling of glass fiber reinforced polymers to find defects. Cirp et al. (2019) simulated the 3D spatial data generated by 3D scanning to provide visualization support for designing manufacturing systems and prototypes. Tao et al. (2020) performed 3D surface scanning of PCB holes based on X-ray micro-CT to check the machining accuracy. *Design by Dragging* (Coffey et al., 2013) provided an interface to design and simulate as straightforward as possible.

5.2. Interactive analysis methods

Interactive analytics methods allow researchers to better analyze image and video data to uncover deeper knowledge. *Tracking & Monitoring* allow analysts to perform analytical research on target objects. In Paramorama prototype (Pretorius et al., 2011), users can select the input parameters of interest and then trace their relationship with the output results. *Exploration & Navigation* analyze the impact between image parameters by panning and zooming the interface, expanding and collapsing the organizational structure. CommunityDiff (Datta and Adar, 2018) used tree diagrams to show the relationships and proportions between the different collection outputs. *Knowledge Externalization* provides a way for researchers to externalize the content of current visualizations. Satkowski and Dachselt (2021) analyzed the impact of visual context on AR in terms of subjective perception and objective measurements using industrial 3D scenes as a background. *Refinement & Identification* facilitate analysts to label data based on known identities. Analysts label high and low-quality results and optimize the search results in Paramorama prototype (Pretorius et al., 2011) (see Fig. 5).

5.3. Application areas

Image and video data exist throughout the manufacturing process. The application of visualization in *Production & Testing* is facilitated by integrating VR and AR technologies with image and video data (Hamid et al., 2014; Satkowski and Dachselt, 2021). In *Analysis & Feedback*, researchers identify product defects, verify machining processes and check equipment installations through visual analysis of image and video data (Cirp et al., 2019; Murithi and Lin, 2020; Tao et al., 2020). By combining an AR headset for monitoring and guidance with a portable tablet device for more detailed data analysis, field operators can respond to major error events in a timely manner and investigate the history of the event to identify causality (Becher et al., 2022; Murithi and Lin, 2020; North et al., 2021; Satkowski and Dachselt, 2021). In *Design & Development*, researchers will summarize the shortcomings in *Analysis & Feedback*, explore the reasons, and then improve the product (Klacansky et al., 2022). In *Education & Training*, to reduce costs, increase interest and facilitate the roll-out of employee training, researchers developed an interactive safety training simulator for a particular industry based on production data and industry safety manuals (Moreland et al., 2019; Pantförder and Vogel-heuser, 2009). Meanwhile, some researchers have also discussed whether the usage of AR in personnel assembly training is justified (Büttner et al., 2020) (see Fig. 6).

5.4. Discussion

Early studies of image and video data focused on 2D data, which may be limited by computer performance and visualization methods. A noteworthy trend can be seen in Fig. 1 that the increasing use of AR and VR from 2019. AR and VR devices have a more interactive nature than screens. Operators wear AR devices with actual production scenes as the background during their inspections, allowing them to visualize the operating data of the equipment (Satkowski and Dachselt, 2021). Similarly, the operator can use the AR device to display possible defects on the product being inspected (Murithi and Lin, 2020). With VR equipments, employees can master the production process and get familiar with the production environment virtually, which improves the efficiency and safety of training (Hamid et al., 2014). In the future, there will be more research based on AR and VR devices, including demonstrating an efficient display of more information and expanded applications of the devices. At the same time, the data dimension has been extended from 2D to 3D. Compared to two dimensions, three dimensions can convey more information. For example, the physical structure of the material and the position of the device in the 3D space. To this end, we hope that volume visualization technologies would be more widely used in manufacturing.

6. Tabular & text data

In this section, we will discuss for tabular & text data in manufacturing processes. Tabular & text data is one of the most common types of multimedia data, which contains structured data, unstructured data and semi-structured data. Structured data is data that can be stored with relational databases and expressed in two-dimensional form. Each row represents an entity, and the attributes of each data column are the same. Unstructured data is data that is organized without pre-defined data models or methods. Text data is one of the typical unstructured data. Semi-structured data is data between structured and unstructured. It does not conform to the structure of the data model associated in the form of relational databases or other data tables, but contains associated tags, semantic elements for delimitation and

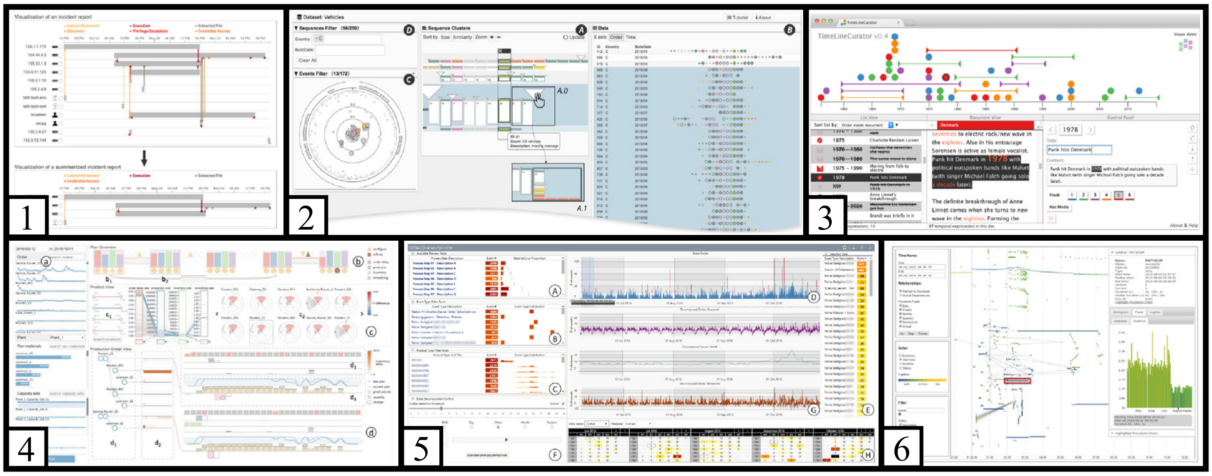

Fig. 6. Visualization of temporality for tabular & text data. (1) Visualization and summary of an incident report (Gove, 2022). (2) Visual analytics system for event sequence data exploration (Chen et al., 2017). (3) Display a timeline of Scandinavian pop music with TimeLineCurator (Fulda et al., 2015). (4) Interface of PlanningVis which supports interactive exploration, comparison and optimization of production plans (Sun et al., 2019). (5) Visual Analytics for Decomposing Temporal Event Series of Production Lines (Herr et al., 2018). (6) Visual monitoring of storage process runs (Meyer et al., 2016).

Fig. 7. Models and algorithms applied to tabular & text data. (1) Automatic visualization answer for natural language questions on tabular data (Liu et al., 2021). (2) A utility-based visualization method for anonymizing multi-attribute tabular data (Wang et al., 2018). (3) Distribution-aware data representation of large-scale tabular datasets for flexible visual queries (Mei et al., 2019). (4) Automatic generation of fact tables from table data annotations (Wang et al., 2019).

hierarchy of records and fields. Therefore, it is also known as a self-describing structure that includes emails, log files, XML files and JSON files. Tabular & text data in manufacturing is large-scale, high-dimensional, and complex relational. The intervention of visualization and visual analytics allows researchers to conduct in-depth analysis of tabular & text data.

6.1. Visualization techniques

Sequence visualization conveys temporality in tabular & text data to users through a special form of visual communication. Depending on the continuity of time, the researchers used lines, curved or straight, to represent time (Bach et al., 2015). To illustrate the variation of data over time, the researchers used time as a dimension in the visualization of both one and two-dimensional forms. In one-dimensional visualization, the data is presented directly on the timeline (Chen et al., 2017; Fulda et al., 2015; Gove, 2022). In two-dimensional visualization, the timeline is represented by x-axis or y-axis in rectangular coordinate (Friedl et al., 2021; Herr et al., 2018; Sun et al., 2019).

Graph visualization is applied to explore the relationships involved in data (Basole and Bellamy, 2014; Klammer and Gmeiner, 2020; Park et al., 2016; Qian et al., 2022; Sharif et al., 2014). In the visual analysis system designed by Park et al. (2016) the graph visualization not only integrates various relevant views and perspectives, but also highlights the different structures of a supply network. Graph visualization was used by Basole and Bellamy (2014) for visual analysis of supply network risk, while *RCDVis* (Qian et al., 2022) was used to interactively detect rare categories (see Fig. 7).

In chart visualization, scatter plots can illustrate the distribution of discrete data (Mei et al., 2019; Yu and Silva, 2016), parallel coordinates can display multi-attribute data (Tang et al., 2022; Yu and Silva, 2016), line and bar charts can show data volume and trend (Oppermann et al., 2020; Sun et al., 2019). *SMART-explore* (Blumenschein et al., 2018) presented high-dimensional data with matrix and heat maps. *McNutt* (McNutt, 2021) made an analysis of table cartograms with algebraic visualization design.

Glyph visualization metaphorically incorporates some attributes of the data in its design (Chen et al., 2017; Sun et al., 2019). *PlanningVis* used timeline based glyphs to present summarized information about various production plans and their differences. By using this glyph view, users can reveal the macro impact of configuration changes, including improving the plan and simulating unexpected events in the market or factory (Sun et al., 2019). Chen et al. (2017) used triangle glyphs to encode the number of event insertions. Users can double-click on the triangle glyphs in the prototype to analyze them in detail.

6.2. Interactive analysis methods

Interactive analysis methods reduce the challenges posed by the large volume, high dimensionality and complex relationships of tabular & text data. *Tracking & Monitoring* allows users to track important information in a highly integrated or information-hidden visual analytics system. *LiveGantt* (Jo et al., 2014) displays detailed information via mouse hover. Meyer et al. (2016) displayed the details of the stored procedure by brushing the target node. *Exploration & Navigation* provides users access to change visualization view. *PlanningVis* (Sun et al., 2019) used drop-down and roll-up of the list to select target dataset. *DataShot* (Wang et al., 2019) extracted a large amount of interesting data from the data table, then mapped the data to visualization elements based on trained decision trees and expressed them externally. It is common for different interactive analysis methods to complement each other in visual analytics systems (Qian et al., 2022; Sun et al., 2019; Yu and Silva, 2016). In *RCDVis* (Qian et al., 2022), users can not only label the nodes corresponding to rare categories for *Refinement & Identification*, but also pan and zoom the node link map for *Exploration & Navigation*.

6.3. Application areas

Tabular & text data of manufacturing is multi-source and mainly applied for *Analysis & Feedback* (Gove, 2022; Mei et al., 2019; Sun et al., 2019; Wang et al., 2018). *RCDVis* (Qian et al., 2022) detected rare categories among graph data by interactive analysis. Gove (2022) proposed a narrative summary algorithm to visualize incident reports and network logs, and its compact representation earned positive reviews from analysts. In *Production & Testing*, properly organizing manufacturing schedules is crucial, and *PlanningVis* and *LiveGantt* (Jo et al., 2014) have conducted extensive work on this topic. In design and development, collected articles focus on how to improve the presentation of tabular & text data. Some of them are related to algorithms (Bartram et al., 2022; McNutt, 2021; Mei et al., 2019), and some to automated generation (Liu et al., 2021; Wang et al., 2019).

6.4. Discussion

In addition to manufacturing, other fields also generate tabular & text data. Despite that data comes from different sources, some visualization and visual analysis methods are versatile. For example, factory production schedules are similar to train schedules which require time series analysis. Content-based text similarity recommendation can be used for maintenance log recording and library book management. With the development of machine learning and artificial intelligence (Yuan et al., 2021), we found that automatic visual generation of tabular & text data is promising. There are also challenges about how to present data and visualize layouts efficiently that need to be addressed urgently (Blumenschein et al., 2018; Mei et al., 2019).

7. Discussion and outlook

In this section, we will make a discussion on the application of multimedia data in the manufacturing industry and provide an outlook on the future of visualization and visual analytics in manufacturing.

7.1. Discussion

In the context of Industry 4.0, the demand for analyzing manufacturing data has increased significantly. Visualization and visual analytics as an effective tool help researchers extract useful and valuable information from the complex and high-volume manufacturing data. In this paper, we review research related to the visualization and visual analysis of multimedia data in manufacturing. We propose a novel taxonomy that classifies multimedia data into *Sensing signal data*, *Image & video data*, and *Tabular & text data* by data type. And then, we discuss them separately in terms of *Visualization techniques*, *Interactive analysis methods*, and *Application areas*. As shown in Fig. 1, we encode the classification basis with different colors. Moreover, through analysis and comparison of related work, we identify trends and recent developments in multimedia data visualization and visual analytics in manufacturing.

The application areas of manufacturing involve several types of multimedia data. As we all know, data of product design is generally *Image & video data*, while user feedback is *Tabular & text data*. Product design requires user feedback as the basis for iterative updates. Two types of multimedia data are involved in *Design & Development*. Visualization and visual analytics as a tool can help researchers reduce the analytical burden associated with multiple data sources and inconsistent data types. Moreover, adding some interactive functions can help researchers discover connections between data to make better decisions. We choose several multimedia data application cases to illustrate the role of visualization and visual analysis.

Digital twin. The digital twin refers to the creation of a digital simulation within an information technology platform by integrating physical feedback data and supplementing with artificial intelligence, machine learning and software analysis. When generating digital twins for particular industries, researchers need to explore five different directions: architecture, modeling, control algorithms, rule models, and physical–digital twin control (Lei et al., 2021). The human–computer interaction problem of digital twin modeling on the Cyber–Physical side and the Cyber–Human side needs to be solved by a digital twin visualization system for flexible manufacturing systems (Fan et al., 2021). In practice, the digital twin data in the manufacturing environment can be visualized with the help of wearable devices (AR), providing operators with more useful and comprehensive information (Zhu et al., 2019).

Location selection. To increase economic benefits, manufacturing industries may shift locations. The selection of locations is determined by several factors. Selecting a warehouse in business districts is a multi-criteria decision that needs to be based on urban road network data, GPS trajectory data, warehouse data, and store data. Visualization and visual analytics can help researchers compare and analyze these data to make the best choice (Li et al., 2020).

Production line. Production lines are the top priority in manufacturing, which generate a large amount of data, including production rate, product quality and equipment status. It is challenging to effectively analyze and extract valuable information from complex production lines (Wu et al., 2018). The visual analytics system, ViDX, supports real-time tracking of assembly line performance and exploration of historical data to identify inefficiencies and anomalies (Xu et al., 2016).

7.2. Outlook

Subsequently, we will discuss and summarize the key challenges and future research in the areas of "Advanced Technology Usage", "Common Visual Analytics Solutions and Processes", and "Multi-Source and Multi-Type Data Fusion Visual Analytics".

Advanced Technology Usage. As representatives of advanced technologies, machine learning and artificial intelligence on the software side and AR and VR on the hardware side have been developed in leaps and bounds. Machine learning and artificial intelligence provide support for efficient processing of multimedia data in manufacturing. Also, a significant amount of research has been done on automatic data understanding and automatic infographic generation. Wearable AR and VR devices are capable of simulating and utilizing actual production environments, increasing the avenues for visual interaction. However, there are several challenges about current usage of advanced technologies as follows. Existing machine learning algorithms are not sufficiently accurate, and AI-based automatic infographic generation often requires human intervention. It remains problematic to accurately model and design reasonable interactions in AR and VR.

Common Visual Analytics Solutions and Processes. Nowadays, there are 31 major categories, 179 medium categories and 609 small categories in China's national economic industry classification. Although there are many subdivision categories, the data types are roughly the same. Therefore, it is essential to design common visual analysis solutions and processes. Visualization and visual analytics can also be used to design system architectures to reduce inefficiencies in the manufacturing process.

Multi-Source and Multi-Type Data Fusion Visual Analytics. Manufacturing processes are composed by several stages and tasks. Each stage interacts with each other in an interlocking manner, which are sources of data generation and produce various types of data. It is worthwhile to investigate how to use multiple sources of multi-type data to discover hidden patterns. In the future, we can design glyphs that display more information. Reasonable visual analysis techniques are also potential solutions.

CRediT authorship contribution statement

Yunchao Wang: Conceptualization, Data curation, Investigation, Methodology, Project administration, Visualization, Writing – original draft. **Zihao Zhu:** Data curation, Investigation. **Lei Wang:** Data curation, Investigation, Writing – original draft. **Guodao Sun:** Supervision, Idea evaluation, Writing – review & editing. **Ronghua Liang:** Guidance, Reviewing, Proofreading.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval

This study does not contain any studies with human or animal subjects performed by any of the authors. All data used in the study are taken from public databases that were published in the past.

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Appendix A. Supplementary data

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