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IVA: A Review of the State-of-the-Art

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ABSTRACT
Industrial machines generate a large amount of data during their production process, which pertains to devices such as motor systems, engine systems, operation recordings, and health information. To present and analyze those data, we have to combine traditional methods like visual analytics with AI, which is called intelligent visual analytics (IVA), to achieve diverse purposes like monitoring and decision-making. This technology combines a group of techniques, such as artificial intelligence, data visualization, and big data, to enable investigators to quickly extract meaningful insights from massive datasets. Thus, we conducted the research to investigate the status and usage of IVA systems, as well as the technologies behind them.

KEYWORDS
Visual Analytics; Machine Learning; AI; IVA

1 Introduction

IVA can help users to explore and analyze data through visual data interaction paired with artificial intelligence, which can even be used to achieve data-driven automatic decision-making. It has become an essential research field of data analytics. Technically speaking, IVA is a research area that composes data visualization, human-computer interaction, and machine learning to gain insights from massive, dynamic, and heterogeneous data[1], which could be depicted in Figure 1. It leverages the strengths of both humans and computers to provide a more effective and resourceful way of comparing to traditional analyses approaches. Other technologies, such as big data, virtual reality, and multi-agent systems, are integrated into visual analytics, resulting in an increasingly rich set of IVA techniques.

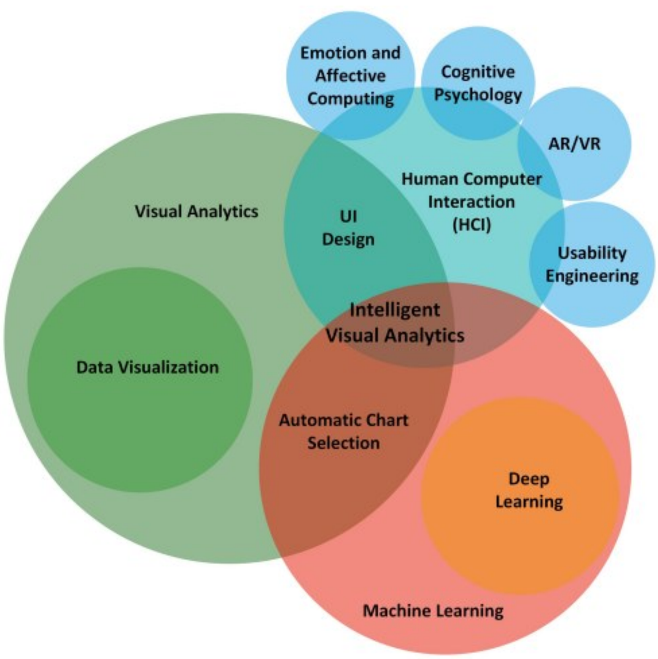

Figure 1 IVA and corresponding techniques

Analyses are usually geared towards data sources of a variety of types, which could be geospatial information, maps, traffic information, natural resources data, text data, or different kinds of sensor data. IVA methods could integrate these data and help researchers achieve pattern recognition, anomaly identification, or make predictions[2]. Such intelligent analyses are usually based on different visualizations and frameworks of big-data architectures, data fusion techniques, and ETL (Extract, Transform, Load) tools as well.

Therefore, this paper is structured as follows: First, we explain what IVA is and its relationship between VA and ML; then we review current studies and surveys on IVA and present the methodology used in this study. Starting from Chapter 3, we focus on different applications that combine AI with visual analytics. Lastly, we summarize the difficulties and future directions of this research.

2 Related Work and Methodology

This report categorizes the selected review papers into two groups: IVA technologies and their applications. Initially, [3] concentrated on examining the integration of machine learning with visual analytics. The primary contribution is to examine the integration of machine learning and data visualization approaches into visual analytics systems. This study highlights two primary functions of machine learning: converting semi-structured or unstructured data into a more comprehensible visual format for human analysis and insight generation, and directing data analysis through various machine learning techniques, mitigating cognitive biases and providing the optimal sequence of steps for visualization, exploration, validation, or knowledge acquisition. The research [4] encapsulates the influence of artificial intelligence on visual analytics. They investigate the application of AI for VA in four primary domains: data processing, analysis, chart selection, and interaction. The paper posits that in the context of intelligent data analysis, deep learning algorithms can assist researchers in selecting appropriate algorithms for enhanced data exploration, contingent upon the characteristics of the data, such as text, image, video, and time series data.

AI use VA as a means of interpretation. Researchers have investigated this topic[5]. Healthcare practitioners must appropriately interpret the assessments of these algorithms to make informed and actionable decisions. According to [2], AI is engaged in healthcare and is progressively employing sophisticated algorithms to analyze extensive data sets and generate predictions. Consequently, visual analytics, which involves human participation in decision-making through the representation of algorithmic interactions, is essential.Secondly, artificial intelligence is significantly influencing research across many engineering disciplines where manual analysis is unfeasible, necessitating the application of unsupervised machine learning for rapid insights. AI-driven computer vision demonstrates exceptional talents and potential in comprehending the real-time dynamics of urban environments. The exponential increase in construction data and the necessity for effective analytical techniques render the research on construction surveillance the focal point of Review[6]. This article analyzes methods including clustering and anomaly detection employed in the monitoring of non-residential structures. It addresses challenges such as interdisciplinary collaboration and data scarcity, proposing solutions through repeatable research and cross-disciplinary cooperation[7]. investigates visual analytics and advancements in visualization within water management initiatives, demonstrating that visual analytics facilitates comprehension of pertinent machine learning techniques through interpretable graphics. The computational model is depicted in Figure 2. They assert that the principal advantage of visual analytics and visualization in big data analysis is in its ability to facilitate feedback loops between computers and humans. Alternatively, [8] examines the evolution of IVA from a supply network viewpoint.

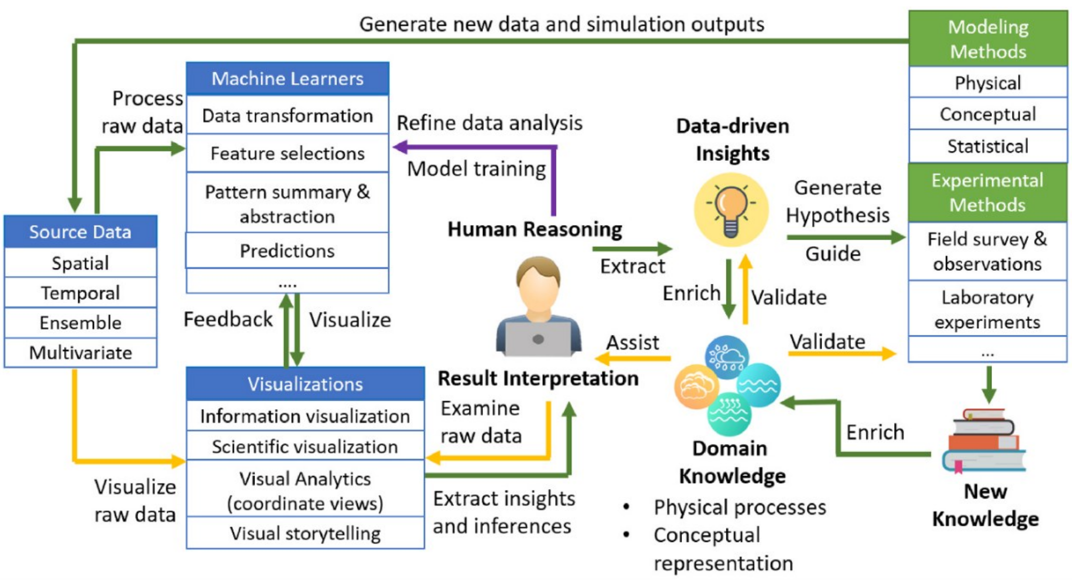

Figure 2 Visual computing pipeline presented by [7]

Research methodology used in this study involved a thorough investigation and analysis of the IVA frameworks. Papers are coming from journals that are indexed by IEEE, ACM, and Science Direct. This search includes topics related to visual analytics, machine learning, intelligent visual analytics, IVA, and other related keywords (e.g., deep learning, computer vision, Industry 4.0, monitoring).

In addition to the preprint repository ArXiv, we have broadened the second search section to include works from conferences including ACM CHI, ACM IUI, Euro Vis, IEEE VIS, and VAST. The data search results for each source and round are compiled in Table 1.

Table 1 Screen Process of the review

Source	Round 1	Round 2	Round 3
ACM	24	11	4
IEEE	285	36	5
Elsevier	176	32	13
Others	260	40	3
Total	745	139	25

3 How machine learning collaborates with visual analytics

Because visual analytics studies employ different raw data and analytical aims, machine learning's role varies.

3.1 Clustering

The research detailed in [9] introduces ClusterLogs, an adaptable and modular error message clustering architecture designed for extensive distributed computing infrastructures. The paper outlines the utilization of a web-based visual analytics tool that enables analysts to visually configure the parameters of the clustering pipeline and aids in the interpretation and validation of the clustering outcomes. In their investigation, several sorts of errors were categorized, and different algorithms were evaluated. Upon assessing several clustering algorithms, they determined that the DBSCAN approach exhibits commendable generalizability, whereas K-means excels in particular contexts. The research demonstrates many categories of error messages using clear scatter plots, as depicted in Figure 3.

Figure 3 Central fragment of visual cluster representation for(a)DBSCAN (b)k-means clustering from [9]

3.2 Anomaly detection

Visual analytics offers the advantage of graphically presenting anomalous data, thus simplifying easier identification and improving the overall analytical intelligence. IVA-based anomaly detection is commonly utilized to assess the condition of an object. For example, in drone surveillance[10], it can be used to swiftly identify abnormal drones, as illustrated in Figure 4. Research encompasses data acquisition via sensors, problem identification and classification through algorithms, and problem representation through visualization.

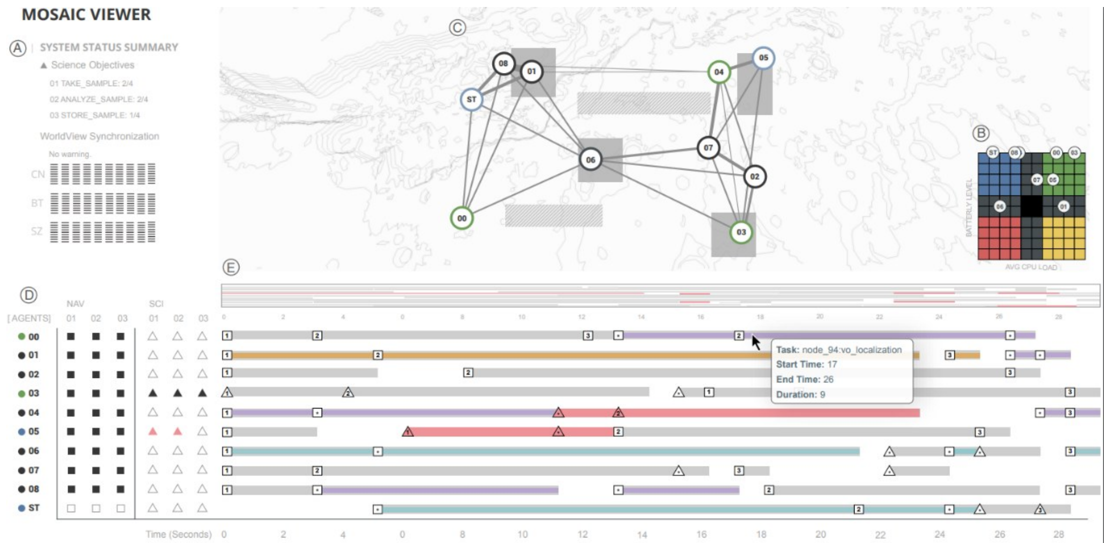

Figure 4 The MOSAIC Viewer as referenced in [10]

The work in [11] addresses multimodal sensors that integrate vibration, acoustic noise, input power, and thrust profiles to identify prevalent problems in Micro Aerial Vehicles (MAVs). The study employs Random Forest (RF) for fault diagnosis in a supervised learning framework, subsequently utilizing the relevant features to conduct two tiers of diagnostics. Their approach generates numerous decision trees during training and produces a verdict based on the mode indicated by the individual trees or an averaged prediction. The research [12] collects extensive and intricate data from sensors aboard underwater drones, and its SubCMedians module has been designed to analyze this data, derive significant insights, and convert them into comprehensible and actionable information, as depicted in Figure 5. It employs an unsupervised learning technique for clustering, which is proficient at identifying anomalies or atypical patterns. In the visual component, they utilize eXplainable Modeling (XM), a Python application that facilitates data analysis and model building procedures. It offers a range of visualizations for data, including time series, heatmaps, 2D/3D scatter plots, boxplots, histograms, geolocation, and t-SNE.

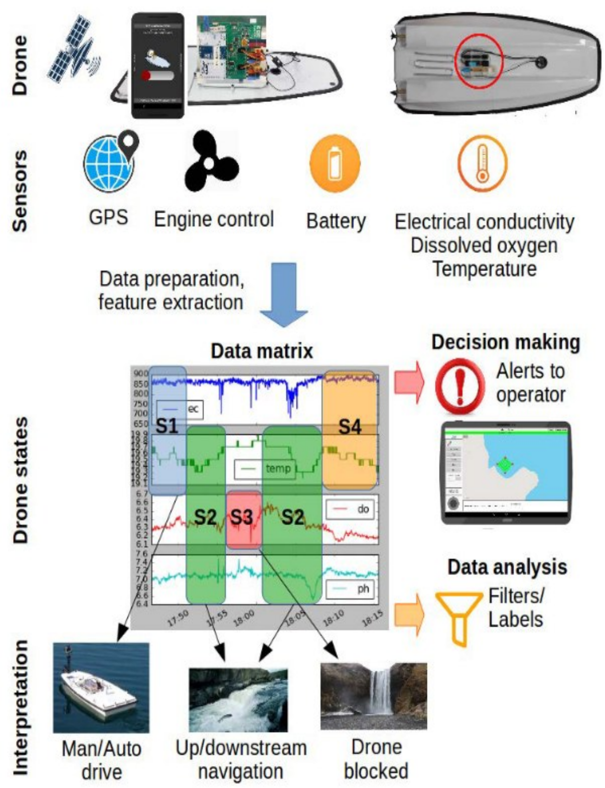

Figure 5 Assessment mechanism for autonomous water drones from [12]

[13] developed the Litho Insight (LIS) visual analytics technology for chip production and processing, which requires early product detection. The LIS platform collects and organizes semiconductor manufacturing data to help engineers understand and improve chip production. It manages large amounts of data from lithography and metrology tools that print and measure patterns on semiconductor wafers and their performance parameters. Their method detects anomalous data using RF and t-SNE. Through performance prediction, LIS may quickly identify and fix semiconductor production defects without direct measurements. [14] uses Convolutional Neural Networks to create Deep Learning (DL) models for bridge flaw identification. Computer vision methods are used to improve bridge inspections, which are laborious and subjective. The Grad-CAM (Gradient Weighted Class Activation Mapping) algorithm is used for visual inspection to evaluate model performance and efficacy on target areas. DeepVATS uses a Masked Time Series AutoEncoder with self-supervised learning [15]. Their technology reconstructs time series segments, allowing the extraction and presentation of major data patterns and anomalies in an interactive graph.

3.3 Predictive analytics

Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) are commonly utilized to extract patterns from previous data, facilitating precise predictions and insights for users. This algorithm works for water resource management in the studies of [9] and [16]. Article [17] employs LSTM to improve understanding of groundwater patterns in the Namoi region. The research uses limited well data readings to offer a clear depiction of the geographical and temporal fluctuations of regional groundwater levels.

[7] emphasizes the difficulty of comprehending and evaluating deep learning models in hydrological modeling. Drawing from recurrent neural network visualization tools, [18] creates a tool that explain LSTM models, showcasing the learning behavior via line graphs and scatter plots. [19] develops a deep learning algorithm utilizing picture data to forecast residential electricity usage. The research utilizes AlexNet for image identification and classification, yielding precise outcomes for developing energy-saving programs. Similarly, [20] uses KNN for power consumption prediction, while [21] used it for predicting the quality of oil.

3.4 Decision making

Machine learning algorithms provide significant real-time visual input for analysis in robots, autonomous vehicles, and complex system management. An novel AUV navigation strategy using a deep learning model and a visual SLAM framework is presented by [22] in UAV navigation research. This strategy improves semantic attribute interpretation in dynamic visual settings. Deep Reinforcement Learning improves autonomous driving navigation by 5%. Some academics use algorithms for decision-making, like [23] with the FairSight system, this field of study is still in its infancy.

4 Challenges and Future Opportunities

The integration of machine learning algorithms is advancing intelligent visual analytics, improving functions from data analysis and chart selection to the display of visual components. This advancement is marked by the management of intricate data, the creation of innovative visualization techniques, interactive dashboards, and the application of augmented reality. Despite these achievements, the field of IVA research continues to encounter several obstacles.

4.1 Multimodal data fusion

As data volumes grow, researchers need tools for macro-analysis and visual analytics on massive datasets. Handling large amounts of interconnected data is difficult. Thus, importing this data is difficult. This makes data storage, combination, and retrieval challenging. Paper [16] presents RHEEM data storage and clever data processing methodologies. Their technology handles Hadoop, DBMS, and Spark data.

4.2 Explainable AI and Visual Analytics

In industries like healthcare, banking, and law, where decisions have serious consequences, people must understand how algorithms make decisions. According to [7], deep learning models like LSTM are difficult to interpret, restricting their use in environmental research, where scientists favor physical models over black-box models. However, eXplainable Artificial Intelligence (XAI) is essential since it clarifies intelligent visual analytics system decisions. Building trust and understanding requires transparency. It involves visualizing model internals and highlighting essential characteristics.

4.3 Nature language query

Complex data might weary or annoy users. As humans communicate primarily in natural language, and natural language interfaces (NLIs) for visual data analysis offer the ability to intuitively express and interact with visualizations. Visual analytics technologies using NLIs allow users to ask queries and get answers quickly. This paradigm was demonstrated by [24], which generated graphs from natural language user questions. The study introduces NL4DV, a Python toolbox for natural language-driven data visualization. This toolkit takes a tabular dataset and a natural language query. It returns a JSON object with data properties, analysis tasks, and Vega-Lite specifications for the query.

4.4 Universal Intelligent Visualization Platform

Most IVA systems use one VA framework and one or more ML approaches without a defined design. The fragmentation of the issue makes IVA development difficult. Scalability is VA's biggest challenge [15]. The availability of various domains and data models with independent virtual assistant solutions hinders knowledge transfer between systems, limiting field improvements. Developers may struggle to build quickly if they lack machine learning or virtual assistant expertise. A flexible framework that can be adjusted for machine learning and graph construction would let developers from many fields create diverse IVA systems. Similar issues were raised by [25].

4.5 Automatic GUI generation

Human operators rely on Google Chart and Amazon Chart to construct new visual analytics interfaces, which is difficult. Creating a chart system independently is complicated, driving research into graphical interface development tools to speed up the creation of varied graphical interfaces. Natural language queries were used to automate chart generation [24]. Since choosing a charting approach is a skill inherent to humans, putting expert knowledge into the system is difficult. The goal is to use machine learning to develop experiential knowledge and automate graph selection. [26] introduces the Compass recommendation engine algorithm, which generates visual recommendations from user preferences, data patterns, and statistical features.

5 Discussion and Conclusion

The review finds many IVA articles on machine learning and visual analytics. Despite guaranteeing article quality and subject coherence, the literature search missed eligible articles and focused on incomplete themes. The assessment notes rapid advances in intelligent human-computer interaction and virtual reality, which are undercovered. IVA has applications in banking, healthcare, business intelligence, cybersecurity, social media, and crime analysis, but not the paper's focus. The paper concludes that ML based visualization is debatable and that specific methods dominate current research. IVA improves analytical thinking by integrating automated analytics with interactive visualization, but it requires knowledge and may misrepresent data. Data quality and completeness restrict visual analytics insights and forecasts. The analysis finds that IVA has promise across industries if data quality and scalable storage options for huge data volumes are improved.

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