Investigation on Works and Military Applications of Artificial Intelligence

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ABSTRACT Technology determines tactics, and tactics promote the development of technology. Artificial intelligence technology is a multiplier that accelerates the innovation and development of military theory. In this paper, we first list the different intelligence levels by introducing their corresponding applications. Then we review the technical classification based on the related concepts, Finally, we discuss technical and practical difficulties and give some solutions from the aspects of strengthening knowledge engineering, building simulation systems, and accumulating data engineering knowledge. The development of Artificial intelligence technology has a profound impact on military development trends, leading to major changes in the forms and modes of war.

INDEX TERMS Artificial intelligence, search methods, machine learning, knowledge engineering, data engineering.

I. INTRODUCTION

Artificial intelligence (AI) is a comprehensive technology involving psychology, cognitive science, thinking science, information science, system science, and biological science. Since the concept of AI was first proposed by John McCarthy at the Dartmouth Conference in the summer of 1956 [1], AI technology has entered a new period of high-speed growth and is recognized as the most likely disruptive technology to change the world in the future. From the victory of "Deep Blue" over Kasparov to the victory of "AlphaGo" over Lee Se-dol [2], machine intelligence has developed from computational intelligence and perceptual intelligence to cognitive intelligence.

The success of AI applications has inspired bright visions and active exploration by a vast number of military researchers. The world's military powers foresee the broad application prospects of AI technology in the military field and believe that the future arms race is in intelligent competition. In the future, AI will play the "intelligent brain" role in Observation, Orientation, Decision, and Action (OODA) because of its high level of military intelligence and widely used tactics. The importance of an "intelligent brain" in

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winning a war is self-evident, and the contribution of an intelligent command system will surpass that of any intelligent weapon. By using AI and other technologies, the consuming time of the whole OODA loop can be reduced, and the goal of command and control in multi-domain joint operations can be achieved, to obtain the right to win in future wars. However, the development of military AI has a long way to go.

In the following sections, starting from the analysis of the level and technology development of AI, we then take a quick review of military AI applications. Approaches in the OODA loop from the aspect of Information Fusion, Situation Awareness, Decision Support System, Path Planning, and Man-Machine Interface. Finally, we present the challenges from the aspect of modeling, information, sample, and evaluation, as well as the corresponding solutions.

II. RELATED CONCEPTS
A. INTELLIGENCE LEVEL

There are three levels of intelligence [3]. Computational intelligence is the ability of fast calculation and memory storage, which is fundamental to perceptual and cognitive intelligence. Computational intelligence applies to domains with clear rules, such as scientific arithmetic tasks and logical processes. At present, computers have already surpassed human beings in computational intelligence.

The supercomputers "Tianhe"[4] and "Deep Blue"[5] are well-known applications of this level.

Perceptual intelligence is the perceptual ability of vision, hearing, and touch, including computer vision, speech recognition, and language translation. Due to the advantage of deep neural networks (DNNs) in the big data era, perceptual intelligence has made great progress and has gradually drawn closer to human abilities. For example, the classification accuracy of ImageNet has surpassed that of human beings [6], and Google Brain successfully "recognized" a cat in a YouTube video after learning 10 million pictures [7]. The accuracy of face recognition has surpassed that of human eyes, and the highest rate of face recognition has reached 99.8%, as announced by Tencent [8]. Besides, gender, age, and emotion recognition are becoming increasingly realistic. In speech recognition systems, the error rate of Microsoft's speech recognition for English is only 5.9%[9] and that of IBM 5.5% [10]. Baidu's [11], Sogou's [12], and iFlytek's [13] speech recognition error rate for Chinese is almost 3%, which is even better than that of human beings at 4%. In a language translation system, Google can translate large sections of text in more than 10 languages [14]. Social chatbots such as Apple's Siri [15] and Microsoft's XiaoIce [16] and Cortana [17] have both an intellectual quotient (IQ) and emotional quotient (EQ), similar to human beings. Other applications, such as Boston Dynamics' "Big Dog" [18], have very flexible and swift reactions that enable them not only to adapt to all kinds of terrain but also to withstand sudden-impact forces and remain stable.

Cognitive intelligence is the ability of understanding, reasoning, and decision-making. NLP is the fundamental technology of cognitive intelligence and has already surpassed the abilities of human beings in specific domains. Based on this, IBM's question-and-answer intelligent program "Watson" achieved remarkable success by winning an unrestricted exhibition match in the competition against humans in Jeopardy!, an American TV quiz show [19]. Currently, research and applications in using cognitive intelligence for various decision-making tasks are spreading. In 2016, AlphaGo beat Lee Se-dol. It was a victory in a complete information game in a limited problem space, where the critical technology was a DNN and Monte Carlo search. Libratus [20] and DeepStack [21] beat top players in Texas poker in 2017 by using recursive reasoning to deal with information asymmetry in peck and a decomposition method to focus calculation on phase. They also used deep learning (DL) technology to automatically learn a kind of "intuition" about any card from self versus an opponent, which was a breakthrough in the problem of an incomplete information single game in a limited problem space. In 2019, AlphaStar defeated professional players in the large-scale real-time strategic game "StarCraft II" [22], which was a milestone in the problem of an incomplete information group games in an open problem space. It made full use of Group Reinforcement Learning, imitation learning, sequential neural network, relation network, convolutional neural network, and an auto-regressive model.

There are still many challenges in meaningful knowledge understanding and conclusion, and the greatest obstacle is how to solve the problem of self-learning since there is a large gap in this capacity between machines and human beings. Other approaches to this problem include IFLYTEK's "CyberBrain Project" [23], Google's "Google Brain", and Google's driverless car [24].

B. TECHNOLOGICAL CLASSIFICATION

Technically, the state-of-the-art method of AI can be divided into search solution, knowledge inference, and machine learning.

1) SEARCH SOLUTION

The representation problem is to further solve the problem, from problem representation to problem-solving, which is a solution process, that is, the search process. In this process, an appropriate search technology, including various rules, processes, and algorithms, is used to find the solution to the problem. The search solution abstracts the decision problem into a set of states and their transition relationships to find the path from the initial state to the final state [25]. Essentially, the search solution can be regarded as a certain type of trial thinking of which the goal is to find feasible/optimal solutions by trying various possible routes. The representative applications are path planning (PP) and board games. The key challenge is that when the solution space is too large, the performance will be greatly reduced or will even be unable to converge to be solved. Therefore, minimizing the number of branches is necessary.

The search finding includes no information search and heuristic search [26]. The no information search includes the Breadth-First Search (BFS), Depth-First Search (DFS), Uniform-Cost Search (UCS), Iterative Deepening Search (IDS), min-max search, alpha-beta pruning [27], and Monte Carlo Tree Search (MCTS) [28]. The heuristic search includes the best-first-search [29] and A∗ search [30].

2) KNOWLEDGE INFERENCE

Knowledge inference refers to the process of using formal knowledge to think and solve problems in computer or intelligent systems by simulating human intelligent reasoning modes and reasoning control strategies [31]. Knowledge inference mainly solves the logical relationship between the premise and the conclusion in the reasoning process as well as the transfer of uncertainty in imprecise reasoning. The knowledge inference process of an intelligent system is completed by an inference engine, which is the program used to realize reasoning in an intelligent system. The basic task of an inference engine is to search the available knowledge in the knowledge base, match it with the database, and generate or demonstrate new facts under the guidance of certain control strategies. Searching and matching are two basic tasks of an

inference engine. A good inference engine should have the following basic required elements: (1) an efficient search and matching mechanism; (2) controllability; (3) observability; and (4) heuristic quality [32].

The knowledge inference of intelligent systems includes two basic problems: the inference method and the control strategy of inference [33]. The inference method studies all logical relations and the law of reliability transfer, while the control strategy is used to limit and narrow the search space so that the original exponential problem can be solved in polynomial time. For problem solving, the control strategy can be divided into three categories: rule learning, an expert system, and fuzzy logic [34].

a: RULE LEARNING

The rule is a kind of objective rule or domain concept that has clear semantics and can describe the data distribution. A rule can be written in the form of "if... then". The rule learning learns a set of rules from training data that can be used to distinguish the rules from the unknown examples [35]. The goal of rule learning is to produce a rule set that can cover as many samples as possible, and the sequential covering is a commonly used scheme. If a new rule is not learned in the initial training set, the training samples for that rule will then be covered, and the remaining training samples will form the training set to repeat the process. Since only a part of the data is processed at a time, this method is also called the divide-and-conquer strategy.

There are two rules in Rule Learning: the propositional rule and first-order rule [36]. In contrast to the propositional rule, which addresses only simple statements, the first-order rule includes assertions and quantification, which can express complex relationships, also known as relational rules. There are two ways to generate rules: the direct method and the indirect method [37]. The direct method directly generalizes rules from the training set, and the indirect method obtains rules from decision tree transformation.

b: EXPERT SYSTEM

Expert System is an intelligent computer program system that contains much of the knowledge and experience of experts in a certain field [38]. It can use the knowledge of human experts and methods to solve problems in that field. In other words, the expert system is a program system with a large amount of expertise and experience. It uses AI technology and computer technology to carry out reasoning and judgment according to the knowledge and experience provided by one or more experts in a certain field and simulates the decision-making process of human experts to solve the complex problems that are usually managed by human experts. In short, the expert system is a computer program system that simulates human expertise to solve domain problems.

An expert system usually consists of six parts: a human-computer interface, knowledge base, inference engine, interpreter, comprehensive database, and knowledge acquisition base [39]. The knowledge base and inference engine are separate from each other. The architecture of the expert system varies with its type, function, and scale.

c: FUZZY LOGIC

Fuzzy logic refers to the uncertainty concept judgment and reasoning mode of the human brain [40]. Fuzzy logic is a science-based on multivalued logic that uses the fuzzy set method to study fuzzy thinking and language forms and the associated laws. When the description system is an uncertain model or the control object has strong nonlinearity and large lag, fuzzy sets, and fuzzy rules simulate the human brain working mode to express transitional boundaries or qualitative knowledge experience and make comprehensive fuzzy judgments.

It is difficult to address the problem of rule-based fuzzy information with conventional methods, but the reasoning mode can manage this process. Fuzzy Logic is good for expressing qualitative knowledge and experience with unclear boundaries. By using the concept of the membership function, fuzzy logic distinguishes fuzzy sets, deals with fuzzy relations, simulates the human brain to implement rule-based reasoning, and solves various uncertainty problems caused by the logic breaking of the "rule of exclusion". At present, research on the combination of neural networks and fuzzy logic has become a very attractive direction in the field of AI [41].

3) MACHINE LEARNING

Machine learning is used to learn implicit models or patterns from massive sample data, which are in turn used to predict or solve practical problems. It includes Supervised Learning, Unsupervised Learning, and Reinforcement Learning [42]. Machine learning can essentially be regarded as a kind of perceptual thinking in which experience intuition can be obtained from massive sample data.

With the help of perceptual thinking, commanders can not only judge the enemy's possible movements and situations but also make rapid decisions based on experience intuition. The problem is that this process is sometimes prone to mistakes when the enemy acts contrary to expectations.

a: SUPERVISED lEARNING

Supervised Learning (SL) refers to the process of adjusting the parameters of the classifier to achieve the required performance by using a set of samples of known categories [43]. SL infers a functional machine learning task from labeled training data. The training data include a set of training examples. In SL, each instance is composed of an input object (usually a vector) and an expected output value (also known as a supervised signal). The structural diagram of supervised learning is shown in Figure 1.

In supervised learning, we usually face a labeled data set $\{x_i, y_i\} \in D$, and we hope to learn mapping $f_\theta : x \rightarrow y_i$, by minimizing the mathematical expectation of the loss
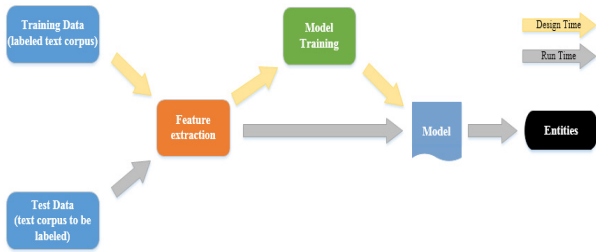
FIGURE 1. Structural diagram of supervised learning.

function $L(f_\theta(x), y)$, which is

$$\theta = \arg\min E_{(x,y)\sim D}[L(f_\theta(x), y)]$$

The SL algorithm is a function of analyzing the training data and generating an inference that can be used to map out new instances. An optimal solution allows the algorithm to correctly determine the class labels of those invisible instances. This requires that the learning algorithm be formed in a "reasonable" way from the training data to the invisible instances. The widely used algorithms are support vector machines [44], linear regression [45], logistic regression [46], naive Bayes [47], linear discriminant analysis [48], decision trees [49], k-nearest neighbor [50], and multilayer perceptron [51].

b: UNSUPERVISED LEARNING

In Unsupervised Learning (UL), the training data are unlabeled, and the training goal is to classify or distinguish the observed values [52]. In essence, it is a statistical method that can identify potential structures in unlabeled data. The structural diagram of unsupervised learning is shown in Figure 2.
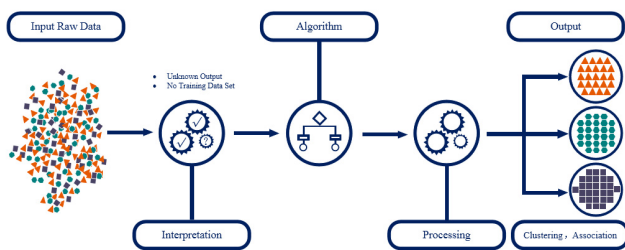

FIGURE 2. Structural diagram of unsupervised learning.

UL is often used in data mining to discover something in a large amount of unlabeled data. For example, UL should be able to distinguish "cat" pictures from a large number of various pictures according to the characteristics of all "cat" pictures without any additional prompts.

There are three kinds of UL: clustering, discrete point detection, and dimensionality reduction [53]. The common UL algorithms are principal component analysis [54], isometric mapping [55], local linear embedding [56], Laplace feature mapping [57], Hesse local linear embedding [58] and local tangent space permutation [59].
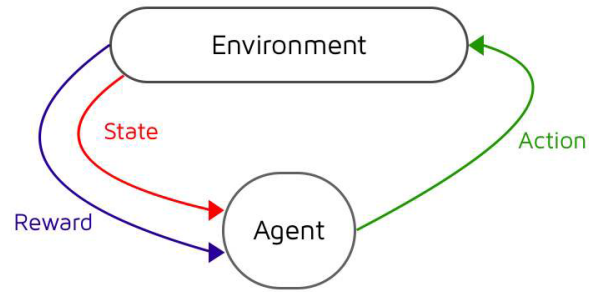

FIGURE 3. Structural diagram of reinforcement learning.

c: REINFORCEMENT LEARNING

Reinforcement Learning (RL) is developed from control theory, statistics, psychology, and related subjects and can be traced back to Pavlov's conditioned reflex experiment. By the beginning of the 1990s, RL technology was being widely studied and applied in the field of AI and was considered to be one of the core technologies in the design of intelligent systems [60]. With breakthroughs occurring in basic research, RL is increasingly being developed and has become a common research focus. The structural diagram of reinforcement learning is shown in Figure 3.

In reinforcement learning, we are faced with an MDP process. We hope to learn a strategy function $\pi_\theta : s \rightarrow a$, by using this strategy function, we can accumulate the maximum mathematical expectation of reward value. For convenience, we record the track generated by using the strategy as τ, and the accumulated reward value as $R(\tau)$, so our optimization goal is:

$$\theta = \arg\max E_{\tau \sim \pi_\theta}[R(\tau)]$$

In SL, positive and negative examples are used to determine what kind of behavior to perform. However, the RLS is different in that it obtains reward (usually a scalar signal) after action from the environment rather than directly telling the system what action to take. As the external environment provides little information, the RLS must learn mostly from its own experience. In this way, the RLS obtains knowledge from the action evaluation environment and improves the action plan to adapt to the environment through trial and error. The abilities of perception and decision-making are both indicators of the intelligence level. It is a long-term challenge for the RLS to directly control agents by learning high-dimensional perceptual input (such as image, voice, etc.) since the quality of the RLS results relies heavily on the quality of state feature selection.

Based on the Markov decision process, RL can be simplified into the form of the following figure. RL has made great progress in the theory and algorithms of strategy selection, such as Monte Carlo [61], Q-learning [62], SARSA [63], TD learning [64], policy gradient [65] and adaptive dynamic programming [66].

d: DEEP LEARNING

The concept of DL originates from research on artificial neural networks (ANNs). A multilayer perceptron with multiple hidden layers is a kind of DL structure. DL combines low-level features to form more abstract high-level representations to discover the distributed feature representation of data. The motivation of DL is to build a neural network to simulate the human brain for analysis and learning. It imitates the mechanism of the human brain to interpret data such as images, sounds, and texts.

DL can be used for SL, USL, and RL in such forms as CNNs, and recurrent neural networks (RNNs) [67] in SL, generative adversarial networks (GANs) in UL, and deep RL (DRL) in RL.

CNN is a kind of feed-forward neural network with deep structure and convolutional computation. It has the ability of representation learning, which enables it to classify input information according to its hierarchical structure by shift-invariant classification. The structural diagram of CNN is shown in Figure 4.
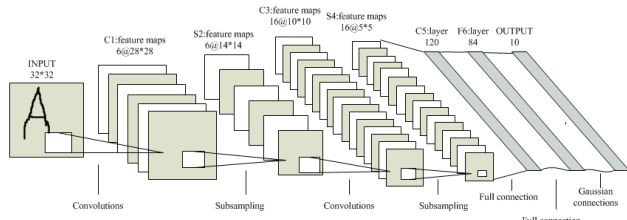

FIGURE 4. Structural diagram of a convolutional neural network [68].

RNN takes sequence data as input and recurses in the evolutionary direction of the sequence so that all nodes are linked in a chain [69]. Research on RNNs began in the 1980s-1990s, and they developed into one of the DL algorithms in the early 21st century. RNN is applied in NLP, such as speech recognition, language modeling, machine translation, and other areas. The structural diagram of the RNN is shown in Figure 5.

The core idea of a GAN comes from the Nash equilibrium in game theory [70]. A generator and a discriminator are designed to capture the potential distribution of real data samples and generate new data samples. The discriminator is a two-classifier system to determine whether the input is real data or generated samples. To win the game, two participants must constantly optimize and improve their generation ability and discrimination ability. This learning optimization process leads to finding a Nash equilibrium between them. A GAN is a two-player game in which the sum of the two players' interests is constant. The structural diagram of the GAN is shown in Figure 6.

DRL can provide a solution to the perceptual decision-making problems of complex systems [71]. AlphaGo is the typical application case of DRL, which is the optimal solution to the optimal decision-making problem of a two-player zero-sum game with complete information.
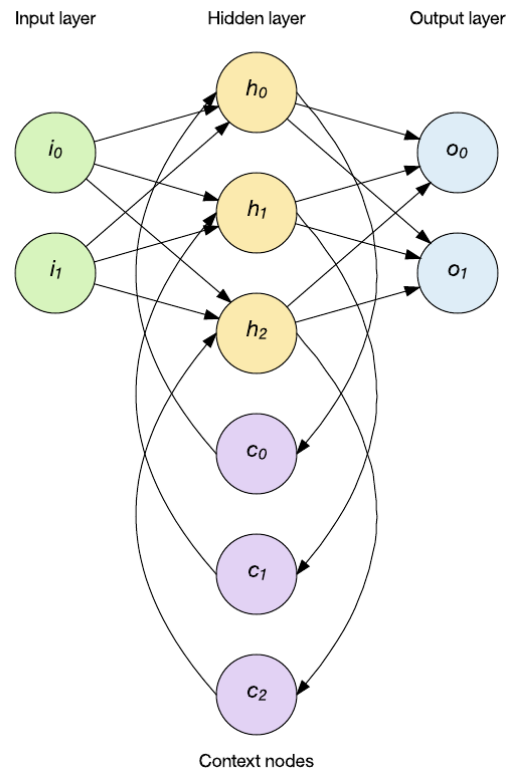

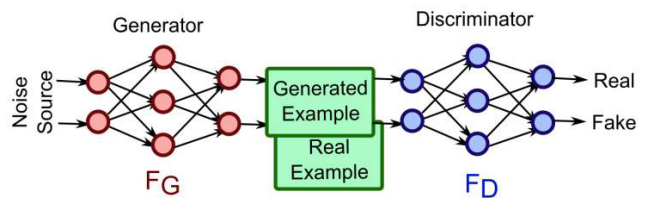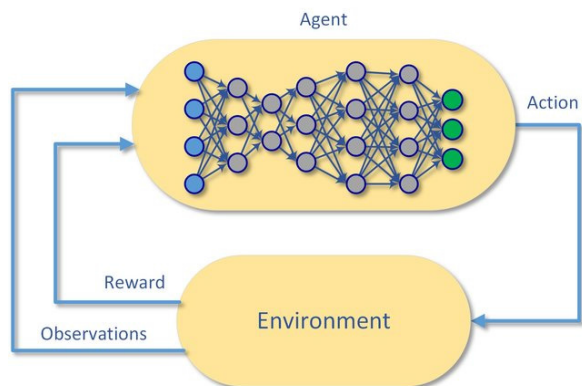**FIGURE 5. Structural diagram of a recurrent neural network.**

FIGURE 6. Structural diagram of a generative adversarial network.

Undeniably, researchers are looking forward to DRL breakthroughs in many other game problems, such as the non-zero-sum game with complete information and multiplayer (multiagent) games (including zero-sum, non-zero-sum, complete information, and incomplete information). The multiagent game is another hot topic in DRL. Foerster *et al.* [72] proposed a deep distributed recursive q-network for the multiagent non-zero-sum game in the process of observable Markov decision-making and successfully learned the communication protocol. The structural diagram of the DRL is shown in Figure 7.

III. MILITARY APPLICATIONS

A. OVERVIEW OF MILITARY ARTIFICIAL INTELLIGENCE

US has always regarded AI as a subversive technology for ''changing the rules of the game''. The US Department of Defense regards AI and autonomy as two technical pillars of the new offset strategy [73], and have kept up with the

FIGURE 7. Structural diagram of Deep Reinforcement Learning.

FIGURE 8. Side view during active combat in Alpha AI. Past and current missile detonation locations marked. Two Blue vs. four Red, all Reds have successfully evaded missiles, one Blue has been destroyed, Blue AWACS in distance [100].

application of machine learning technologies in decision support [74]. In the early 1960s, the Defense Advanced Research Projects Agency (DARPA) developed a computer time-sharing operational technology program to begin the initial research on machine learning [75]. By the mid-1970s, DARPA had become the main supporter of machine learning research in the US and promoted the practical application of machine learning technology, such as automatic speech recognition and image processing [70]. In the 1980s, international research on computer systems increased [76], and the US army felt that their dominant position in the field of computing was increasingly threatened. Therefore, in 1983, DARPA established strategic computing (SC) project to retain its supremacy in the field of computing and information processing, with AI as a basic component of SC [77]. The relevant research includes the tactical mobile robot (TMR) [78] project, mobile autonomous robot software (MARS) [79] project, and software of distributed robot (SDR) project and distributed robot (DR) [80] project. In the 1990s, after the concept of the decision support system was proposed [81], US army developed a series of decision support systems, such as the Joint Operation Planning and Execution System (JOPES) [82], Combat Evaluation Model (CEM) [83], Joint WARfare System (JWARS) [84], Joint Theater Level Simulation (JTLS) [85], RAND Strategic Assessment System (RSAS) [86], Computer-Aided Mission Planning System (CAMPS) [87], Joint Mission Planning System (JMPS) [88], and Staff Plan and Decision Support System (SPADS) [89]. These systems were applied in military actions, such as "Desert Storm" in the 1990s [90]. Functions from simple cargo airlifts to complex operational coordination were performed by these expert systems.

In 2007, DARPA launched the "Deep Green" plan [91], which aims to embed simulation in command-and-control systems to improve the speed and quality of a commander's onboard decision-making. The fundamental idea is very similar to that of AlphaGo, that is, real-time generation and updating of multibranch game trees that can reflect all possible future situations and simulation of the results of fighting along each branch to realize the pruning and searching of the

game trees. However, due to the technical conditions at that time, the "Deep Green" plan was only partially successful.

In recent years, DARPA successively launched a large number of basic machine learning technology research projects, exploring and developing related technologies of independently obtaining and processing information, extracting key features and mining association relations from different types of multisource data, such as text, image, sound, video, and sensor [92]. In 2015, the US military launched the "Commander's Virtual Staff" (CVS) program [93], which provides decision-making support for army commanders and their staff in the process of making operational plans. In June 2016, the "Alpha AI" air combat simulation opponent pilot developed by the University of Cincinnati of the US won a victory over the famous air force tactical instructor Colonel Gene Lee [94]. Side view during active combat in Alpha AI is shown in Figure 8. In April 2017, Robert Walker, the designer of the "The Third Offset Strategy" of the US, first proposed the concept of "Project Maven [95]". He hoped that by tapping the enormous potential of AI algorithms for situational awareness, intelligence analysis, command, and decision-making, combat action and other aspects, he could solve the problems of war attack and defense in an algorithmic way to achieve the goals of winning in war and serving political aims. Starting in 2018, DARPA planned to invest two billion US dollars to reshape the application of AI technology in the military field over the next five years in a project called "AI Next [96]". This project includes five directions: new AI capability, robust AI, anti-AI, high-performance AI and next-generation AI. In June 2018, the US Department of Defense established the Joint AI Center [97], which is responsible for constructing military AI and promoting research on key machine learning technologies in the "Project Maven". In 2019, US army invested 72 million dollars in Battlefield AI projects with many universities [98], such as Carnegie Mellon, to study AI technology in the military field with the aims of greatly improving combat effectiveness by enhancing soldiers' capabilities, optimizing operational guidance, improving agility and reducing casualties. Among the new projects in the DARPA 2020 budget, the first one is to continue to

strengthen AI application research in the military domain, focusing on the development of a new learning structure [99].

B. APPROACHES TO OBSERVATION, ORIENTATION, DECISION, AND ACTION

1) INFORMATION FUSION

Information fusion (IF) is also known as data fusion, which can comprehensively process multisource information and knowledge to obtain a more accurate and reliable description and understanding. Different kinds of multisource IF are the premise of situation assessment. IF can correctly describe different aspects of a target or event and provide more profound and complete environmental information through reasoning. Multisource IF generally adopts a three-layer fusion structure: data layer fusion, feature layer fusion, and decision layer fusion. It includes classical reasoning, Kalman filtering, and expert systems [101].

As a potentially powerful but immature technology, IF provides a broad application field and research space. At present, more intelligent methods are being applied to IF, including fuzzy theory, neural networks, and wavelet analysis theory [102]. The combination of IF and AI has shown great advantages and thus has become a research and development direction in the fields of data fusion and AI.

2) SITUATION AWARENESS

Situation awareness (SA) is the perception and understanding of environmental elements in the depth of time and space, the understanding of the intentions of other agents, and the inference of the state trend to be developed [103]. With the development of information technology, the mode of war has changed from single combat to integrated joint combat, meaning the unification and coordination of all combat units. Owing to the characteristics of joint combat, such as a multidimensional combat space, multiple combat forces, and unified battle command of the overall operation, commanders must have real-time command of the battlefield. The ability to acquire knowledge of the battlefield situation depends heavily on a variety of battlefield awareness systems.

It is vital to process the fused information to form situational knowledge and understanding that reflects the current situation and then transmit them to the driver and other systems. The entire operational process, such as sensor management, assistant decision-making, and man-machine interface (MMI) management, relies on the quality of SA [104].

3) DECISION SUPPORT SYSTEM

The decision support system (DSS) uses various quantitative models to support semi-structured and unstructured decision problems [105]. DSS requires the participation of decision-makers. Employing human-computer dialogue and manipulation of data, it supports the structured and clear parts of the decision-making process. In the process of task implementation, when the environment is changing rapidly, the objects and problems of decision-making are often uncertain and fuzzy.

The intelligent DSS (IDSS) is a combination of AI and DSS technology that enables a DSS to make full use of human knowledge, such as descriptive knowledge about decision-making problems, process knowledge in the decision-making process, the reasoning knowledge needed to solve problems, and an auxiliary decision-making system to help solve complex decision-making problems through logical reasoning. The concept of IDSS was first proposed by Bonczek et al [106]. in the 1980s. Its function is to deal with both quantitative and qualitative problems. The core idea of IDSS is to combine AI with related scientific achievements to provide a DSS with AI. AI technology is introduced to a DSS mainly through combining ES and DSS by adding an inference engine and rule base to the DSS system. In the process of decision-making, much knowledge cannot be represented by data or models, so there is no fixed way to apply expertise and historical experience. The rule base of an IDSS can store this knowledge and provide an important reference and basis for decision-making. An IDSS with model analysis can support decision-making with quantitative analysis. AI technologies, especially those with knowledge reasoning, are the core of qualitative analysis ability.

4) PATH PLANNING

PP is used to avoid threats or obstacles [107]. According to the suggestions of an intelligent tactical DSS, waypoints should be provided for fulfilling a task to help commanders choose the appropriate path. However, emerging threats and obstacle avoidance also require the ability to respond quickly and reasonably. Therefore, it is necessary to have a fast and reasonable PP ability to achieve goals at the cost of an optimized path.

Common research on PP includes V graph-based planning [108], genetic algorithm-based planning [109], dynamic planning, and A∗ algorithm-based planning. A common characteristic of these methods is that when the planning is extended to three dimensions, the algorithm faces the challenges of a large amount of data and slow convergence speed. Therefore, this area has become a research hot spot.

5) MAN-MACHINE INTERFACE

MMI technology provides a good environment for communicating with an assistant through hardware equipment [110]. In the interaction process, the operator can not only be continuously inspired and guided but also feel natural and comfortable. By creating a "human-computer cohabitation" environment, an intelligent auxiliary system becomes the operator's staff and assistant.

The principle of MMI is to provide the right information in the right way at the right time, with the main characteristics being intelligence and graphics. From the perspective of the commander's understanding, graphics are easier to understand than text or data tables in terms of information content, expression, access, intuition, and speed of

understanding since humans receive information mostly from vision. Therefore, how to provide the commander with as much information as possible through the limited interface is an important consideration.

C. CHALLENGES AND SOLUTIONS

Although AI has many applications and methods in the military field, there are still many difficulties that we resort to simulation systems, knowledge engineering, data engineering, and coordination to conquer.

1) COMPLEX SYSTEM MODELING

There is too much battlefield information, including combat units and weapon equipment, in warfare. The modeling is much more complex than that of real-time strategy games. How to consider macro-level abstract modeling and the rationality of detailed factors is a research direction. Such considerations are more complex for unit behavior control, battlefield environment, mechanism of action, and evaluation criteria. In many cases, war has no single unique target, and the purpose of the confrontation does not need to be battled out. For example, the capture of sea power and air power, the ratio of war efficiency and cost, the war damage rate, and the sustainability of resources are also criteria for determining the "winner" of a war. At the same time, the military serves political goals. If a war achieves only its military purpose but is politically and economically passive, the result will not be a victory. On the other hand, a war, even if it fails militarily, can be said to have resulted in a strategic victory if political and economic containment is achieved.

The simulation system environment is a relatively simplified, effective, and ideal environment for verifying and evaluating the level of intelligence. Under the same conditions of a military scenario and operational rules, through offline training and online human-machine confrontation and machine-machine confrontation, the winning rate or battle damage ratio is used to measure the level of intelligence. From the perspective of development, the difficulty of building the bottom layer is relatively low, and the difficulty of building the simulation system from the platform/tactical level and gradually extending it to the higher campaign and strategic levels is greater. Compared with the strategic and campaign levels, the tactical action level model has clear behavioral boundaries, clear rules, and more training data.

2) IMPERFECT INFORMATION SETTINGS

As Sun Tzu said, the mutant is ever victorious [111]. However, in a confrontation situation, the information obtained is always limited, and the authenticity of the information is not guaranteed. How to make decisions with such imperfect information and ensure the maximum benefit requires comprehensive trade-offs. A confrontation is different from a Go game, and the action and state continuously evolve. How to discretize time and action, create temporary advantage windows, and seize, retain and use initiatives to achieve military or strategic goals need to be studied. There is

no fixed form of recruitment or method of moving troops in the confrontation environment. The belligerents cannot play according to the routine but must act according to circumstances within a certain range of choices. They also must pay attention to contingencies and innovate their tactics as needed.

AI technology is not omnipotent. It needs to be combined with traditional technologies, such as knowledge reasoning and search and solution, in which the role of domain knowledge is indispensable. Domain knowledge refers to facts and rules that can be explained clearly by military experts, including military domain concept ontology, weapon equipment performance parameters, battlefield environment models, battlefield entity models, battle decision models, business processing rules, battle law application rules, and equipment use rules. The knowledge of the military domain is very professional. Not only military experts who are familiar with particular operations but also engineers with a certain technical background are needed to participate in the establishment of formal representations and topological relationships so that the machine can understand and master the information. The US military has always attached great importance to knowledge engineering and has built a complete knowledge system of regulations and rules of engagement. The famous knowledge engineering CYC project is a typical case [112].

3) SMALL SIZE AND LOW QUALITY OF SAMPLE

The excellent performance of AI depends mainly on data fitting and parameter optimization on large samples, which requires high-quality samples. At present, there are great difficulties in the sources of sample learning, from tactics to action plan generation. First, in terms of the number of samples, even US army that has the most abundant cumulative actual combat experience are still experiencing the problem of the number of machine learning samples that can be provided by short-term and strong confrontation environments being too small, which makes it difficult for AI to perform in the confrontation environment. Owing to the incompleteness and inaccuracy of information about potential adversaries, it is impossible to obtain actual combat data; besides, the data samples obtained from training exercises are limited by security and cost, and there is a large gap between exercise and real life in terms of intensity, flexibility, and equipment. Also, the exercise data sometimes have only a single sample type and uneven sample distribution.

Given the lack of actual combat sample data, it is suggested that the gap be filled in the following two ways of parallel development: first, collect the accumulated data from the actual use of command-and-control systems, invest in technical personnel to carry out labeling work, apply diversified labels to the data based on the needs of various machine learning tasks, and build a data-label database. Second, learn from the idea of the US air force to build a simulated flight environment for alpha training or to quickly accumulate large-scale command-and-control sample data through real-time strategic games. In the simulation environment, the commander

can play unlimited roles, the action execution process can be completed quickly, and the scenario and scenario can be flexibly customized on-demand, which can not only train the commander but also test the tactics and accumulate sample data.

4) LACKING MEANS OF EVALUATION

The core of military intelligence is decision-making using intelligent technology with learning ability. How to verify these technologies is the key to sustainable development. As we know, science and technology are a double-edged sword, which may speed up R&D and catch up with others but may also fail miserably in practice. The results obtained from expert scoring and other traditional objective methods are not suitable. The generalizability and reliability of the evaluation AI algorithm in the process of assistant decision-making need to be verified under the premise of a large number of simulation experiments, and the functions need to be tested.

Besides, we should broaden our research ideas and strengthen cooperation with the outside world. First, cooperation with universities should be strengthened. Colleges and universities are rich in AI teachers with convenient foreign exchange, broad academic vision, and weak pursuit of profits. They are reliable partners for armies to realize military intelligence and move towards world-class AI systems. Second, cooperation with AI companies should be strengthened. Local AI companies are flexible and diversified and can fully mobilize the resources of all parties. Through the establishment of cooperative alliances, such as the rapid response group of national defense science and technology innovation, and the use of advanced commercial technology to serve the military, they should promote the formation of a flexible and efficient military intelligence innovation value chain to accumulate experience and promote integrated military-civilian development in the field of military intelligence.

IV. SUMMARY

Science and technology are the most active and revolutionary factors in military development. The development of AI technology has a profound impact on military development trends, leading to major changes in the forms and modes of war. It has not been long since military powers truly began to experience breakthroughs in intelligent technology in the military field, and no substantive breakthrough has been made above the tactical level. To face up to the difficulties, it is urgent to identify opportunities, refuse to advance rashly, start from the foundation, and gradually research military intelligence level by level.

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